EXPLORING THE SOCIAL AND SPATIAL CONTEXT OF ADULT OBESITY IN AOTEAROA NEW ZEALAND: A SPATIAL MICROSIMULATION APPROACH

A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy in Geography at the University of Canterbury

by Alison F. Watkins

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In memory of my grandmother,

Jane Fern Barbour

1925 - 2013

Acknowledgements

"A journey of a thousand miles begins with one step"

-- Lao Tzu

The first step in my case was an email to Jennifer Brown, who would later become one of my supervisors. The second was a reordering of everything I thought I knew about New Zealand. The third was a trip of around one thousand kilometres — not miles — from Auckland to Christchurch. The story of the rest is written in this thesis. It hasn't been an easy journey. It never is. But, more than ever, I am grateful for and humbled by the opportunities that have led me to journey here.

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Abstract

Obesity rates have risen substantially in recent decades. A large body of research links excess body fat to a variety of health conditions including cardio vascular disease (CVD), certain cancers, and non-insulin-dependent diabetes mellitus (NIDDM). Research also indicates that recent social and economic change are among the underlying causes of the 'obesity epidemic.' Aotearoa New Zealand exhibits one of the highest obesity rates in the Organisation for Economic Co-operation and Development (OECD). Reducing obesity in New Zealand is therefore a priority for policy makers.

Existing research demonstrates that the burden of obesity is not evenly distributed in Aotearoa New Zealand. Obesity rates are highest among Māori and Pacific Peoples, and those living in the most socially deprived areas, neither of which are evenly distributed spatially.

Sampling constraints mean that standard statistical methods are unable to estimate obesity rates at a spatial scale smaller than at the District Health Board (DHB) level. Yet fine-scale estimates of obesity would help to understand the distribution of obesity at neighbourhood level and thus provide policy makers with a tangible tool to target and combat obesity. Neighbourhoods in Aotearoa New Zealand vary across the regions of the country so to rely on large scale statistics for decision-making risks overlooking small pockets that would benefit from targeted assistance.

The aim of this thesis is to put population level adult obesity in New Zealand into a spatial context using spatial microsimulation modelling (SMSM). SMSM is a technique that combines detailed microdata from the New Zealand Health Survey (NZHS) with small area census data to generate obesity estimates at a neighbourhood level.

There are three key findings in this thesis. First, obesity is clustered into a spatially confined subset of areas, primarily associated with high deprivation mediated by age and ethnicity. Second, a broad range of obesity rates were estimated for small areas, varying from 15.3% to 67.2%; these estimates of obesity in 2013 are novel and not available through other sources.

Third, projections from the model for 2018 and 2023 predict only small changes in obesity rates, yet a widening of obesity related health inequities.

The SMSM outputs will be useful for operational policy decisions as well as informing policy more broadly. Collectively, the work presented here extends the understanding of the geography of obesity in Aotearoa New Zealand.

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Glossary

Acronym	Explanation
ACC	Accident Compensation Corporation, national no-fault accident insurer.
BMI	Body Mass Index, calculated by: (weight in kilograms)/(height in metres)^2.
CAU	Census Area Unit, the second smallest census geography used in Aotearoa New Zealand. Officially called ‘Area Units’, the C is added to avoid confusion with the general term area unit.
CO	Combinatorial Optimisation, a SMSM methodology.
CURF	Confidentialised Unit Record File.
CVD	Cardio vascular disease.
COPD	Chronic obstructive pulmonary disease.
DHB	District Health Board, used to refer to either a board of elected officials and or the regions they represent.
GP	General Practitioner a primary health care doctor, or general practice.
GWR	Geographically Weighted Regression.
HAES	Health at Every Size.
HEHA	Healthy Eating — Healthy Action, an anti-obesity intervention.
HIA	Health Impact Assessment.
HiAP	Health in All Policies.
IPF	Iterative Proportional Fitting, a SMSM methodology.
IDI	Integrated Data Infrastructure
LFS	Labour force status.
LGA	Local Government Act.
LTMA	Land Transport Management Act.
MB	Meshblock, the smallest census geography used in Aotearoa New Zealand.
MELAA	Middle Eastern, Latin American, and African, an ethnicity grouping used for census data in Aotearoa New Zealand.

Acronym	Explanation
NDAI	Neighbourhood Destination Accessibility Index, a tool developed by Witten, Pearce, and Day (2011).
NIDDM	Non-insulin-dependent diabetes mellitus, also known as type 2 diabetes. Note that the more general term ‘diabetes’ has been used where different types of diabetes cannot be differentiated.
NILF	Not in Labour Force (an abbreviation for one level of the labour force status variable).
NZ	New Zealand.
NZDep	New Zealand Deprivation Index.
NZHS	New Zealand Health Survey.
NZiDep	New Zealand Index of Individual Deprivation.
NZTA	New Zealand Transport Authority.
OECD	Organisation for Economic Co-operation and Development.
PHO	Primary Health Organisation, provide primary health care.
PHU	Public Health Unit, provide regional public health services.
Qual	Qualification.
R	R, statistical software.
RC	Regional Council.
RMA	Resource Management Act.
RMSE	Root mean squared error.
SAE	Standardised absolute error.
SEI	Standard error about identity.
SES	Socio-economic status.
SMSM	Spatial microsimulation model(ling).
Stats NZ	Statistics New Zealand (recently changed officially to Stats NZ).
TA	Territorial Authority, city or district councils.
TAE	Total Absolute Error.
UDS	Greater Christchurch Urban Development Strategy
UK	United Kingdom.
USA	United States of America.
VDR	Virtual diabetes register.
WHO	World Health Organisation.

Chapter 1 Overview

It has become commonplace in mainstream media to be confronted with hyperbolic headlines about the ‘obesity epidemic’, often accompanied by exhortations to eat less and exercise more, or warnings of related disease. In contrast, the academic literature on obesity is full of conflicting advice (e.g. Blair, Archer, & Hand, 2013; Luke & Cooper, 2013b), complexity (e.g. Moore & Cunningham, 2012), critique (e.g. Evans, 2006), and controversy (e.g. Stanhope, 2016).

Despite the level of interest from the public and the substantial amount of published research, there are still critical gaps in the knowledge of obesity in Aotearoa New Zealand, particularly around the spatial distribution of obesity. This thesis will address the lack of small scale estimates of obesity rates by combining data from the New Zealand Health Survey (NZHS) and Census data to generate a spatial microsimulation model (SMSM).

The purpose of this chapter is to provide a brief introduction to the thesis. The chapter begins with an overview of the context of the research (Section 1.1), followed by the problem statement (Section 1.2). Next, the aims and scope of the thesis are outlined, along with the research objectives (Section 1.3). Finally, the chapter will conclude by outlining the structure of the thesis (Section 1.4).

1.1 Research context

Aotearoa New Zealand has among the highest rates of obesity in the Organisation for Economic Co-operation and Development (OECD), 30.7% in 2015, exceeded only by Mexico and the United States (OECD, 2017). However, the burden of obesity is not distributed evenly among individuals; the highest rates are found among those living in areas of low socio-economic status (SES), as well as Māori and Pacific Peoples (Ministry of Health, 2016a). Existing research establishes links between obesity outcomes and different types of environments, including both the built and social environment (Egger & Swinburn, 1997; Ivory et al., 2015; Pearce & Witten, 2010b).

The influence of the environment on obesity makes it important to gain a better understanding of the spatial distribution of obesity. However, obesity estimates using conventional statistical methods are available only at national or District Health Board (DHB) scale due to methodological limitations (Ministry of Health, 2012b, 2015d). DHBs are large, administrative health units used to organise health care in Aotearoa New Zealand, and obesity estimates at a finer scale than this would be beneficial in the development of obesity policy. Fine scale obesity estimates would facilitate the identification of small pockets of obesity which might otherwise be overlooked in large scale figures, as well as better illustrating the rates of obesity in local communities (Openshaw, 1984a).

SMSM is a technique which combines small area Census data with detailed survey microdata using variables common to both data sets (called constraints). The resulting model is, in effect, a synthetic population which resembles the Census but contains non-census variables of interest (such as obesity or diabetes) from the microdata sample (Ballas, Rossiter, Thomas, Clarke, & Dorling, 2005c). In using this type of model, it is possible to see obesity estimates at a neighbourhood scale, examine key subpopulations, pose ‘what if’ policy questions, and generate population projections for future time periods.

SMSM offers important technical and informational advances in the knowledge of obesity in Aotearoa New Zealand, but caution is required during the interpretation of the model results. Obesity is highly stigmatised and framed as amoral (LeBesco, 2011), and even with the best of intentions medical and public health approaches can easily result in ‘blaming the victim’ or render individuals as ‘helpless victims of an obesogenic environment’ (Adler & Stewart, 2009).

In a specifically Aotearoa New Zealand context, there are strong associations among Māori and Pacific ethnicities, low SES, and obesity, as well as acknowledged differences in body structure among different ethnic groups (Ministry of Health, 2016a; Rush, Freitas, & Plank, 2009; Theodore, McLean, & TeMorenga, 2015). Consequently, care must be taken to avoid reproducing existing social inequities among these groups.

1.2 Problem statement

As described previously (Section 1.1), the rate of obesity in Aotearoa New Zealand is high. Obesity is associated with variety of health conditions including cardio vascular disease (CVD), certain cancers, and non-insulin-dependent diabetes mellitus (NIDDM). In addition, obesity poses a substantial cost to both individuals and the public health system, estimated at NZ$135 million in 1991 dollars (Swinburn et al., 1997). As a consequence, the Ministry of

Health has identified obesity among its priority actions in the *New Zealand Health Strategy: Roadmap of actions 2016* (Ministry of Health, 2016b).

Although obesity is considered a significant and important public health issue, current knowledge of its spatial distribution is limited to DHB level statistics. Obtaining information about the spatial distribution of obesity at smaller spatial scales is hampered due to the data requirements for conventional frequentist or Bayesian statistics. Specifically, these methods require a sufficient sample from every small area, which SMSM does not. As Aotearoa New Zealand has a diverse and spatially heterogenous population, this coarse spatial scale is inadequate for understanding obesity and related diseases in Aotearoa New Zealand.

Current understanding of obesity and related diseases in Aotearoa New Zealand could be improved through small area estimates of obesity rates. The fine scale of small area obesity estimates would provide the Ministry of Health with another tool for use in formulating obesity policy. Small area estimates open the possibility of using obesity as a covariate in models to site a new treatment centre, targeting health promotion campaigns, or provide additional support to general practice (GP) clinics. The deeper understanding of the spatial distribution of obesity gained from this thesis can be used to better inform policy through a greater understanding of the background context.

The main argument in this thesis is that the DHB level estimates of obesity available through conventional statistical methods are insufficient to properly understand the impact of obesity on Aotearoa New Zealand communities. This thesis presents a SMSM (SimAotearoa[1]) which allows estimation of obesity rates in small areas. SimAotearoa will increase understanding of obesity in Aotearoa New Zealand in four ways: (1) through providing a finer scale picture of overall obesity and diabetes, (2) detailed investigation of obesity in key population subgroups such as Māori, or Pacific Peoples, (3) estimating future changes in obesity rates, and (4) through evaluating the implications of the model for policy and society.

1.3 Aims and scope

The aim of this thesis is to put population level adult obesity in Aotearoa New Zealand into a social and spatial context using SMSM. The purpose of the research is to provide the Ministry of Health with important information that will support operational policy and

[1] Aotearoa is the te reo Māori name for New Zealand.

decision-making on obesity and related diseases, as well as inform obesity policy development more broadly. The scope of the thesis includes the whole adult population of Aotearoa New Zealand — children aged under 15 years are out of scope.

1.3.1 Objectives

To meet the aim of the thesis, five specific objectives were developed. These are listed below. Table 1.1 shows where in the thesis each objective will be addressed.

1. To review the literature around obesity and obesogenic environments, and the use of spatial microsimulation for health purposes.
2. To develop a spatial microsimulation model (SimAotearoa) suitable for estimating adult obesity and diabetes at a small area level in the Aotearoa New Zealand population in 2013; and to test the validity of this model.
3. To develop a spatial microsimulation model (SimAotearoa) that estimates future adult obesity rates based on 2018 and 2023 population projections; and to test the validity of this model.
4. To explore the results of both static and projected spatial microsimulation models for obesity, diabetes, and key population subgroups, including how these results may be potentially relevant to policy.
5. To evaluate and critique the outputs and potential uses of SimAotearoa.

Table 1.1: Concordance of objectives and chapters

Objective	**Chapter**
1 (Literature Review)	2 and 3 (Literature Review, Aotearoa New Zealand context)
2 (Model design and validation)	4 (Design and validation)
3 (Projected model)	6 (Projections)
4 (Exploration of results)	5 and 6 (Spatial patterning of obesity, projections)
5 (Evaluation)	7 (General discussion)

1.4 Thesis structure

The objective throughout this thesis is to establish spatial variation in obesity prevalence as an important area of endeavour in geographic research, and SMSM as a useful methodology for investigating this. The remainder of the thesis is structured as follows.

Chapter 2 addresses existing literature on obesity and obesogenic environments. It begins with a brief overview of the obesity epidemic and why addressing obesity is important. Following this, the measurement of obesity and competing explanations for the underlying causes is addressed. The chapter goes on to review current research on obesogenic environments and establishes the gap in current research on obesity in Aotearoa New Zealand which can be addressed using SMSM. The chapter concludes with a background on SMSM and how it has been used thus far for health and obesity related research.

Chapter 3 provides a brief introduction to the Aotearoa New Zealand context. This short chapter addresses the geography of Aotearoa New Zealand, its social context, the health system in Aotearoa New Zealand, current obesity estimates for the country, and a description of the Census and survey data that will be used. Some aspects of society, public health and Census data in Aotearoa New Zealand are distinct from similar countries, and this chapter is expected to be of use to international readers.

Having established the context for the research, Chapter 4 describes the design and validation of the SimAotearoa model, including further details of the data and SMSM methodology used. The results of the model validation will be presented here. The methodology evolved as the model was developed in order to best suit the needs of the data and model, therefore the methods are discussed alongside the conditions that led to their use rather than being contained in a separate chapter.

With the validity of SimAotearoa established, the outputs will be analysed in Chapter 5. This chapter will initially cover basic estimates of obesity, overweight, and diabetes. Subsequent sections will address more detailed analysis of the results, including comparisons with deprivation, and obesity estimates for key population subgroups.

Chapter 6, the final results chapter, presents the projected model of obesity for 2018 and 2023 using SimAotearoa. This model builds on the model constructed in Chapter 5 and uses many of the same methods, with the distinct methodology used for this projection described within the chapter.

Chapter 7 provides a general discussion and critique of the results as a whole. This begins with an assessment of the technical details of SimAotearoa, its validation, limitations, and how this may apply to future SMSM research in Aotearoa New Zealand. The chapter moves on to discuss the implications of the findings from SimAotearoa with respect to society and policy in Aotearoa New Zealand.

Chapter 8 concludes the thesis. It presents an evaluation of the research objectives, and the key points made. Additionally, it identifies potential future research, and makes recommendations for the Ministry of Health regarding policy.

Chapter 2 Literature Review: Obesity and the contribution of spatial microsimulation modelling

Obesity is the medical term for excess body fat. The World Health Organisation (WHO) report defines obesity as *"a condition of abnormal or excessive fat accumulation in adipose tissue, to the extent that health may be impaired"* (2000, p. 6). In recent years, the prevalence of obesity has grown substantially leading to the description 'the obesity epidemic' (Pearce & Witten, 2010a; World Health Organisation, 2000). It is this rapid rise in obesity rates that has made obesity a topic of interest for scientists, health professionals and laypeople.

The purpose of this chapter is to provide background context for the research and demonstrate how SMSM can be useful for understanding obesity and developing obesity policy in Aotearoa New Zealand. This chapter will address Objective 1: to review the literature around obesity and obesogenic environments, and the use of spatial microsimulation for health purposes.

The chapter begins with a discussion of what the obesity epidemic is and why it is a problem (Section 2.1). This is followed by a discussion of the measurement of obesity, the limitations of current methods, and some possible causes of obesity at an individual level (Section 2.2). The following section will discuss an alternative explanation for the rapid rise in obesity rates — the 'obesogenic environment' — this section will also establish the gap which can be filled by SMSM (Section 2.3). Finally, the chapter will examine the uses of SMSM for public health (Section 2.4).

2.1 The obesity epidemic

Medical researchers argue that obesity is now so prevalent and increasing so rapidly that it is an epidemic. Though the precise origins of the phrase 'obesity epidemic' are ambiguous, and its appropriateness is in dispute, it is used to describe the rapid rise in obesity rates around the world during the latter part of the 20th Century and early 21st Century (Caballero, 2007;

Flegal, 2006). Despite this recent focus, obesity was identified as a potential risk to health as early as Hippocrates (Bray, 1990).

The purpose of this section is to establish why obesity is a worthy topic of study. This section is structured as follows: Sub-section 2.1.1 will outline the background of the obesity epidemic, its history Sub-section. This will be followed by a discussion of obesity patterns in developed nations (Sub-section 2.1.2), and migration patterns in the Asia-Pacific region which may affect obesity in Aotearoa New Zealand (Sub-section 2.1.3). Sub-section 2.1.4 will address the use of BMI and potential biases introduced by how obesity is defined. Finally, Sub-section 2.1.5 will examine some of the reasons why obesity is a problem.

2.1.1 Fifty years (or more) of expanding waistlines

The origins of the obesity epidemic stretch back much earlier into the 20th and even 19th Centuries than is generally recognised. Caballero (2007) identified gradually improved nutrition resulting in increases in both height and body weight throughout the 19th and into the 20th Centuries, with the growth in body weight gradually overtaking increases in height in the early 20th Century. Bua, Olsen, and Sørensen (2007) identified similar trends among children in Denmark: stable obesity rates through the 1930s and 1940s (but increasing rates of overweight), then increases in obesity rates until the mid-1950s, followed by another plateau until the mid-1960s and then a second period of increasing rates. Despite the early origins of the rise in body weight, obesity was not widely recognised as an important health issue until the 1960s at which time it was associated with the rise in cardio-vascular disease (Caballero, 2007). In Europe, the increase in obesity rates lagged somewhat behind the United States of America (USA) and it is associated with the end of post-war rationing (Lang & Rayner, 2007).

Throughout much of human history, obesity was associated with high social status due to the scarcity of food for most of the population (Caballero, 2007). The movement from restricted diets where obesity was associated with wealth, to relatively unrestricted, calorie dense diets where obesity is associated with social deprivation has been termed the ‘nutrition transition,’ and is associated with globalisation (Popkin, 1994). Less developed countries tend to exhibit the earlier part of the transition, where obesity is more associated with high social status and there may be severe under-nutrition among those of lower social status (though this can vary with urbanisation); thus these countries can experience a ‘double burden’ of obesity and malnutrition (Popkin, Adair, & Ng, 2012). Developed countries, like Aotearoa New Zealand, exhibit the second, later part of the transition with obesity most common among those of low SES.

In Aotearoa New Zealand, the Ministry of Health (2004b) identified slow growth in obesity rates throughout the 1970s through until the mid-1980s. Obesity rates were around 10% in the late 1970s, whereas by 2002/03 rates were above 20% and now exceed 30% (Ministry of Health, 2004a, 2004b, 2016a). However, it is worth noting that this report indicated that the evidence suggested that the origins of the obesity epidemic in Aotearoa New Zealand predated the earliest available data (1977). Additionally, the report identified a socio-economic gradient in obesity prevalence that was evident among females during earlier time periods than males, but is now present for both genders.

Barry Popkin and colleagues have suggested a number of potential causes for the obesity epidemic (e.g. Bray & Popkin, 2014; Popkin & Gordon-Larsen, 2004). These include increasing dietary energy density, increasing consumption of animal products, increasing consumption of sweeteners including sugar, and decreasing energy expenditure (Popkin, 1994, 2010; Popkin & Gordon-Larsen, 2004). Social, economic, and behavioural changes over the last 50 years are commonly identified by medical researchers (including Popkin) as facilitating these alterations in eating and exercise behaviours and consequently obesity (e.g. Lang & Rayner, 2007; Popkin et al., 2012). However, the link between these factors and body weight is problematic, as will be discussed later in this Literature Review (see Sub-sections 2.2.2, 2.2.3, and 2.3.5).

2.1.2 Developed nations

Of particular interest for this study is the concentration of obesity amongst lower socio-economic groups in developed nations. A recent international review demonstrated that the association of low SES with high obesity rates is predominantly driven by a social gradient among women in developed countries, with few significant associations found among men (McLaren, 2007). An earlier study found that the social gradient of obesity among women in developed countries drove the overall relationship between SES and obesity to a greater extent, suggesting that the gendered nature of this relationship is weakening (McLaren, 2007; Sobal & Stunkard, 1989). However, Aotearoa New Zealand data runs counter to this trend, with a socio-economic gradient emerging among males from 2003 (Ministry of Health, 2004b). Diets of low SES individuals in the developed world are less restricted than is seen in the developing world; thus obesity among low SES individuals is associated with factors known to increase fat deposition, such as stress (Moore & Cunningham, 2012), and energy dense diets (Drewnowski, 2009), see Sub-section 2.2.2 for further discussion.

Minority ethnic groups are more likely to experience socio-economic deprivation, and thus also poorer health outcomes including obesity. However, even at comparable SES levels, health outcomes of minority groups are often poorer than dominant groups (Dressler, Oths, & Gravlee, 2005; Zhang & Wang, 2004). This is partially a result of historic inequities such as colonialism, but also ongoing inequities such as racism (Harris et al., 2012; Theodore et al., 2015). Dressler et al. (2005) highlight psychosocial stress and structural-constructivist models as offering the greatest potential to explain these health disparities. In Aotearoa New Zealand, this picture is complicated by differing body composition among Māori and Pacific Peoples causing artificially high obesity estimates using WHO BMI categories (Rush et al., 2009), as will be discussed later in Sub-section 2.1.4.

In Aotearoa New Zealand, obesity rates are highest among those living in the most deprived areas, and those of Māori and Pacific ethnicity, according to the most recent NZHS[2] (Ministry of Health, 2016a). The overall obesity rate in the report was 31.6%, a small increase since 2011/12, with the rates among Māori and Pacific Peoples much higher — 47.1% and 66.9% respectively. As mentioned previously, this is partially a result of differing body composition among different ethnic groups against a single set of BMI categories, but it is also related to the over representation of Māori and Pacific Peoples among the most deprived groups.

2.1.3 Migration patterns

Aotearoa New Zealand is home to a large migrant population, and given the ethnic differences in obesity rates migration patterns are of interest for this review. For the year ended June 2017, total net migration was 72,300; the four largest source countries for migrants were Australia, the United Kingdom (UK), China, and India, though the first two of these include many returning citizens of Aotearoa New Zealand (Stats NZ, 2017c). In 2007, the largest source region for migrants who were not citizens of Aotearoa New Zealand was Asia (28.8%), closely followed by Europe (27.1%); migrants from the Pacific made up 10.1%

[2] At time of writing.

of the total (Statistics New Zealand, 2009a). Aotearoa New Zealand has specific migration streams for Pacific migrants, so this is a relatively constant stream of migrants (MBIE, 2016).

There are differences between migrants and the extant population of the host country, which may be lost over time. Many countries, including Aotearoa New Zealand, have health requirements for migrants (Immigration New Zealand, 2017). However, the initial healthy status of migrants can change over time with exposure to the culture and habits of the host country (Delavari, Sønderlund, Swinburn, Mellor, & Renzaho, 2013). The impacts of this are not consistent among different groups of migrants, and may vary with age, gender, ethnicity, length of residence, etc. (Delavari et al., 2013).

Obesity rates vary throughout the Asia-Pacific region, generally higher among Pacific Island nations, and lower in Asia. One study identified Oceanic countries[3] as having the largest increase in age standardised mean BMI over the period 1980 to 2008, and included countries with the highest average BMI values (Finucane et al., 2011). However, a small number of lower obesity nations in this group meant that the region did not have the highest obesity prevalence overall (Finucane et al., 2011). This would suggest that migrants from some parts of the Pacific are likely to arrive in Aotearoa New Zealand with a high BMI, but others may not. Conversely, though obesity among Asian ethnic groups is much lower, South Asians (e.g. Indians) in Aotearoa New Zealand are much more likely to be obese or diagnosed with NIDDM than East/South East Asian (e.g. Chinese, Indonesian) groups (Parackal, Smith, & Parnell, 2015). Thus, the obesity related health status can vary among subgroups of migrants to Aotearoa New Zealand.

It is also worth noting that Aotearoa New Zealand, among other nations, may have an impact on the diet of Pacific Peoples even before they arrive here as migrants. The export of unhealthy foods like ‘mutton flaps’ as food aid has a substantial impact on diets in the Pacific (Hughes & Lawrence, 2005; Zimmet, 2000). The World Health Organization (2003) found some evidence among Pacific Islanders that those who consumed imported food were more likely to be obese. This is supported by other studies. In one example, Cassels (2006) found that contact with other nations has modified diets in the Federated States of Micronesia,

[3] Cook Islands, Fiji, French Polynesia, Kiribati, Marshall Islands, Micronesia (Federated States of), Nauru, Palau, Papua New Guinea, Samoa, Solomon Islands, Tonga, Vanuatu

beginning with early explorers in the late 1800s, and including more complex recent interactions such as foreign exploitation of local fisheries (Cassels, 2006).

2.1.4 To BMI or not to BMI?

Very accurate measurements of body fat can be obtained using laboratory-based methods, but these require equipment that is too large for the average clinical setting, or survey participant's home. These methods include dual-energy x-ray absorptiometry, underwater weighing, air displacement, and total body water (Lohman & Milliken, 2003). They are sometimes used in medical or health related studies (e.g. Goonasegaran, Nabila, & Shuhada, 2012; Jackson et al., 2002; Rush et al., 2009). However, they are not used for assessing obesity in the Ministry of Health's main survey — the NZHS (Ministry of Health, 2012b).

There are a number of more practical and portable methods for measuring obesity in a non-laboratory setting. These include skin fold thickness, waist circumference, waist to hip ratio, body mass index (BMI), and bioelectrical impedance (Lohman & Milliken, 2003). Each of these has its own flaws and limitations. Skin fold thickness shows considerable variation between observers, making its usability limited. The two waist measurements do not distinguish between different types or locations of fat, though waist circumference does capture abdominal fat, which is more strongly associated with NIDDM and CVD and thus can be a useful complementary measure. BMI does not distinguish between fat and other types of body mass. Bioelectrical impedance is no more accurate than anthropomorphic measurements, but requires a specific piece of equipment. It is very important that anthropomorphic measurements be carried out by a trained interviewer or clinician, as there can be substantial variation between BMI values based on surveyor measured and self-reported data, and this can have substantial effects on the results (Ezzati, Martin, Skjold, Vander Hoorn, & Murray, 2006; Le et al., 2014).

Though other alternatives to BMI have been suggested, they are not yet widespread reducing comparability between studies (e.g. Nevill, Duncan, Lahart, & Sandercock, 2017). Consequently, it is simpler, cheaper, and more comparable to use anthropomorphic measurements, generally either BMI or a waist measurement (Kopelman, 2000; Lohman & Milliken, 2003). The majority of this thesis will use BMI categories to determine obesity categories because this is the standard used by the Ministry of Health, and thus what is most useful for policy applications at the present time (Ministry of Health, 2008a, 2015a).

BMI is calculated by dividing weight (in kilograms) by height (in metres) squared giving an index with values in kilograms per square meter. An example of how to calculate BMI for an individual weighing 65 kg and standing 170 cm tall is given in Equation 2.1 below.

$$\frac{65\ (kg)}{1.7^2\ (m^2)} = 22.5\ kg\ m^{-2} \qquad \text{Equation 2.1}$$

BMI is the measure recommended by the WHO, and consequently is the measure most often used to clinically classify obesity (World Health Organisation, 2000). The same report identifies intra-abdominal fat as a particular issue, yet BMI does a poor job at distinguishing this from other forms of body mass, as discussed above. The WHO obesity categories are shown in the first column of Table 2.1. There are additional categories that indicate increased risk of comorbidities: obese class II at BMI values 35.0 to 39.9, and obese class III at BMI values of 40.0 or more (World Health Organisation, 2000). These additional classes have not generally been used in this thesis as they are not commonly used in the obesity literature other than for clinical purposes.

Table 2.1: Ethnicity specific BMI categories.

Category	WHO	Māori, Pacific	Asian
Underweight	<18.5	<18.5	<18.5
Normal weight	18.5-24.9	18.5-25.9	18.5-22.9
Overweight	25.0-29.9	26.0-31.9	23.0-27.4
Obese	>30.0	>32.0	>27.5

Note: the WHO categories are used for all individuals. This table is based on Rush et al. (2009); WHO Expert Consultation (2004); World Health Organisation (2000).

Different BMI categories have been calculated for different ethnic groups, including Asian, and Māori or Pacific (Table 2.1). This is because these ethnic groups can show markedly different levels of body fat at the same BMI value (Rush et al., 2009; Swinburn, Ley, Carmichael, & Plank, 1999b; WHO Expert Consultation, 2004). Using ethnicity specific BMI categories causes problems due to issues of comparability[4] and because of the complications that arise when trying to select a categorisation for individuals of mixed ethnicity, but using

[4]There are no ethnicity specific categories for children, and comparisons between countries or studies using different category definitions are much more difficult.

the single set of categories as recommended by the WHO results in an increase of around 11% in the proportion of Māori and Pacific adults classified as obese (Ministry of Health, 2008a). The WHO recommends the use of a single set of cut-off points for all adults (the WHO standard), regardless of ethnicity, thus the WHO categories have been used in this thesis. Thus, it is important to bear in mind the potential inaccuracies of this approach, and that it will necessarily overestimate obesity rates among Māori and Pacific Peoples and underestimate obesity among Asian populations.

The major criticism of BMI is that it cannot distinguish between muscle or bone and fat mass. Consequently, BMI consequently fails to account for differences in body type and composition, such as the effects of ethnicity (described above), sex differences in body composition, or the changes in BMI that result from aging (Rothman, 2008). There are also issues around whether obesity is predictive of related health outcomes (Rothman, 2008). Another example is that athletes are commonly classified as overweight or obese by BMI despite being physically fit simply because muscle is heavier than fat (Rothman, 2008). In particular, the *Body Size Technical Report* for the 2006/07 NZHS specifies that:

> *"For individuals, BMI should not be relied on as the sole indicator of body fatness or disease risk; factors such as body fat distribution and other risk factors or co-morbidities should also be taken into account."* (Ministry of Health, 2008a, p. viii)

There is a growing awareness amongst the general public of the flaws in BMI. A few studies have used laboratory methods to compare with BMI measurements (e.g. Goonasegaran et al., 2012), including NHANES 2005-06 which was illustrated in popular media (Sun, 2015). Comparisons have also been used to critique the use of BMI for the study of obesity (Rothman, 2008). Though the limitations of BMI as a metric for obesity are widely known, the lack of a simple alternative measure keeps it in wide usage. The usual suggestion to mitigate the effects of this is to take it into account when interpreting results. Despite these attempts, the results of such analyses still reproduce structural inequities — in Aotearoa New Zealand, this is particularly evident among Māori and Pacific Peoples for whom BMI is known to overestimate obesity. The WHO categories also underestimate obesity in the Asian population, a limitation often overlooked due to the low obesity rates in this group (WHO Expert Consultation, 2004).

Despite the difficulties outlined above, BMI remains the accepted standard for assessing obesity in official surveys in Aotearoa New Zealand. Thus, it will be used in the analyses presented later in this thesis for comparability purposes. However, the limitations outlined above mean that caution must be exercised in the interpretation of the results.

2.1.5 Why worry about obesity?

Obesity is associated with a wide variety of other medical conditions. These include: NIDDM, CVD, gallstones, certain cancers, hypertension, asthma, obstructive sleep apnoea, arthritis, endocrine and metabolic disturbances such as insulin resistance, gout, and psychological issues (Popkin, 2010; Swinburn et al., 1997; World Cancer Research Fund, 2007; World Health Organisation, 2000; Young, Peppard, & Gottlieb, 2002). Indeed, obesity is considered to be a risk factor for many of these non-communicable diseases, though they may take many years to develop detectable symptoms. So, a significant part of the human cost of obesity is in the risk of more serious co-morbid conditions and the associated negative health outcomes. Obesity is also associated with reduced life expectancy (Flegal, Graubard, Williamson, & Gail, 2005; Turley, Tobias, & Paul, 2006).

In terms of costs to the health care system, the illnesses that develop as a result of obesity must be treated. A 1997 study estimated the costs of obesity to the health system in Aotearoa New Zealand at NZ$135 million in 1991 dollars (Swinburn et al., 1997). This is approximately NZ$225 million in 2017 dollars[5]. An additional consideration not considered by Swinburn et al. (1997) is the need for specialist equipment in order to safely care for very large patients (Hahler, 2002). In addition to the costs to the health care system, one study found that obese individuals have medical costs roughly 30% higher than comparable normal weight individuals (Withrow & Alter, 2011).

There are also social costs associated with obesity. Obesity is highly stigmatised and obese individuals face discrimination in a variety of settings, including from health professionals (Puhl & Heuer, 2009; Schafer & Ferraro, 2011; World Health Organisation, 2000). This stigma cannot be overcome by high social status (King et al., 2014). Another consideration is that changing patterns of body size alter perception of what is normal; for example Etelson,

[5] From 1991 Q3 to 2017 Q3 using the Reserve Bank of New Zealand Inflation Calculator: https://rbnz.govt.nz/monetary-policy/inflation-calculator.

Brand, Patrick, and Shirali (2003) found that parents of overweight children did not recognise that their child was overweight.

There is some debate about whether obesity is the cause of ill-health (as described above), or merely a symptom of other health issues (Campos, Saguy, Ernsberger, Oliver, & Gaesser, 2005; Evans, 2006). There is evidence that metabolic disease can develop independently of obesity, which would support this view (Stanhope, 2016). Another possibility is presented by Gronniger (2005), who demonstrated that living in a household with an obese person presents a comparable risk of mortality to being obese oneself. Logically, having an obese family member ought to have no effect on mortality, yet Gronniger's (2005) work demonstrates that it does. The relationship between 'familial obesity' and mortality suggests that obesity may be merely an indicator for some other factor or combination of factors in the physical, social or economic environment that cause obesity and have health impacts on related individuals whether they are obese or not (Gronniger, 2005). Even if obesity is primarily a symptom of ill-health, its rapid rise in prevalence represents a substantial and concerning inequity[6].

There are many different kinds of harm that result from obesity. Some of these are modifiable (e.g. discrimination), some are not — beyond reducing the incidence of obesity (e.g. the cost of equipment to care for large patients). Reducing or eliminating these harms should result in more equitable health outcomes, particularly considering the strong association between obesity and low SES in Aotearoa New Zealand. Thus, reducing obesity is one potential way to improve the equitability of health outcomes in Aotearoa New Zealand.

2.2 Beyond energy balance: Causes of obesity

The previous section provided a brief overview of the history of obesity, some of the patterns associated with it, how it is measured, and established why it is a problem. This section covers possible causes of obesity.

It is important to consider individual level factors which may impact on how obesity can be modelled, as well as the accuracy, framing and interpretation of such a model. When constructing a population level model, it is impossible to consider the specific circumstances and features of every individual in the population, even when working at very fine scales.

[6] The term 'inequity' has been used throughout this thesis in preference to 'inequality' with few exceptions, as in most cases the unequal distribution of health or resources being described is unfair, preventable, and greater than can be explained by determinants such as SES. See also Kawachi, Subramanian, and Almeida-Filho (2002).

The real world is far more complex than any model which can realistically be built. Complex models may offer greater accuracy, but this does not guarantee that they will be useful; often a generalisation — while less accurate — may be more useful. For both practical and computational reasons, a model must always be an approximation.

This section is structured as follows: Sub-section 2.2.1 examines energy balance as a model for the development of obesity in individuals and discusses some of the issues with this as an explanation for the obesity epidemic. Next, Sub-section 2.2.2 introduces a broader picture of the causes of obesity. The final two sub-sections address the stigmatisation attached to obesity and its implications for public health (Sub-section 2.2.3), and impacts on policy and population level analysis of obesity (Sub-section 2.2.4).

2.2.1 The old lie: Energy balance

The most prominent explanation for why individuals become obese is that of an 'energy imbalance' (Hill, Wyatt, & Peters, 2012; World Health Organisation, 2000). Specifically, where intake of energy — food — exceeds energy expenditure, both in terms of physical activity and base metabolic function, with the excess converted into fat (World Health Organisation, 2000). This is in accordance with the first law of thermodynamics, that the energy in a closed system is constant. Hill et al. (2012) use this idea to frame the argument that body weight cannot change if the two sides of the equation (intake and expenditure) are in balance. The WHO attributes the idea of human metabolism obeying the law of thermodynamics to the work of Lavoisier in the 19th Century (World Health Organisation, 2000). However, describing obesity solely as a matter of energy balance is a dangerous over-simplification of a very complex problem. This sub-section and the next serve to highlight the complexities of addressing obesity; understanding the drivers of obesity is important to building the model later in the thesis.

The energy balance model is very open to being framed as a problem of personal responsibility and is often attributed to 'poor lifestyle choices' (Jenkin, Signal, & Thomson, 2011; Kwan, 2009). The frames of energy balance and personal responsibility readily become entangled with neoliberal political ideology (Warbrick, Dickson, Prince, & Heke, 2016), and it is readily apparent that the energy balance frame has been adopted by the food and beverage industry, alongside arguments that attempt to deflect the need for regulation (Brownell et al., 2010; Jenkin et al., 2011; Kwan, 2009). It is partially from the personal responsibility frame that the stigmatisation and discrimination discussed earlier in Sub-section 2.1.5 arise (Brownell et al., 2010).

The food and beverage industry have taken steps to fund research that supports the personal responsibility frame, and by extension their products and business model. An illuminating series of debate and commentary papers were published in the *International Journal of Epidemiology* in 2013. The series began with an initial paper (Luke & Cooper, 2013b) arguing that physical activity has no impact on the risk of obesity, and was followed five responses: one neutral (Swinburn, 2013), four disagreeing (Blair et al., 2013; Fisher, Hunter, & Allison, 2013; Hill & Peters, 2013; Wareham & Brage, 2013), and an authors' response (Luke & Cooper, 2013a). Two of the most vehement of the dissenting articles were written by authors who declared funding from the food and beverage industry:

> *"We disagree and contend that to support their position Luke and Cooper misrepresent and/or ignore an extensive evidence base of observational and experimental studies that clearly support an effect of PA [Physical Activity] on obesity..." (Blair et al., 2013, p. 1836)*

> *"So much science is missing here and it is difficult to believe the paper was reviewed by anyone with expertise in exercise science. Why not?" (Hill & Peters, 2013, p. 1842)*

Luke and Cooper (2013a) acknowledge that their analysis was imperfect, but also question why these two authors emphasise a single study; one with a high participant dropout rate. The other two dissenting papers presented more balanced, qualified opinions stating that *"exercise is beneficial for weight loss if the exercise programme is adhered to"* (Fisher et al., 2013, p. 1847) and *"Although the evidence concerning activity and weight gain is weak, it is not so weak that the current public health guidance should be altered"* (Wareham & Brage, 2013, p. 1844). Conflicts of interest have a demonstrable effect on the conclusion of scientific papers relating to the food beverage industries (Bes-Rastrollo, Schulze, Ruiz-Canela, & Martinez-Gonzalez, 2013; Canella, Martins, Silva, Passanha, & Lourenço, 2015; Lesser, Ebbeling, Goozner, Wypij, & Ludwig, 2007; Palma, Ferreira, Vilaça, & Assis, 2014). Studies reporting potential conflicts of interest with the food industry are more likely to report findings favourable to that industry and less likely to report associations with obesity than comparable studies without conflicts of interest (Bes-Rastrollo et al., 2013).

Taking into account the impact of conflict of interest on the dissenting commentaries then the series of papers mentioned above support the idea that while physical activity has a positive impact on *health*, it has an equivocal impact on *obesity* benefitting some individuals but not others. The volume and vehemence of the argument that if people would only eat less and exercise more, they would easily lose weight appears to be driven by industry. Yet this is the argument that is most visible and understandable to the general public (Jenkin et al., 2011; Kwan, 2009).

Though the energy balance model has some merit — the body does store excess energy as fat for later use — it fails to account for the vast array of other influences on metabolic function even while acknowledging the complexity of the system (e.g. Hill et al., 2012). This complexity was recognised in the WHO's expert consultation on obesity:

> *"In contrast to the widely held perception among the public and parts of the scientific and medical communities, it is clear that obesity is not simply a result of overindulgence in highly palatable foods, or of a lack of physical activity."* (World Health Organisation, 2000, p. 101)

Some of the mechanisms involved have been known to medical and scientific researchers for some time. For example the influence of stress on metabolic function (Moore & Cunningham, 2012), and the potential for a genetic contribution to weight gain (Burgio, Lopomo, & Migliore, 2015). However, in recent years other causal mechanisms for weight gain have been identified, including epigenetic factors (Burgio et al., 2015), or the gut microbiome (Ley, Turnbaugh, Klein, & Gordon, 2006). The next section will address these causes.

2.2.2 Underlying causes

If energy (im)balance plays only a small part in determining body weight, then what other causal factors are or are not involved? Understandings of the relationship between an individuals' body and weight is still developing. What is known illustrates that it is an extremely complex relationship. In contrast to the predominantly individualised explanations of the preceding section, many of the underlying causes of obesity arise from the structural environment beyond the influence of individuals. Modelling the underlying individual causes is beyond the scope of this thesis, but understanding what they are and how they may affect individuals is important for understanding obesity on a population level as well.

Though genetic abnormalities play a role in the development of obesity in individuals, genetic factors have been ruled out as a cause of the recent widespread increases in obesity rates (Smith & Cummins, 2009; Swinburn et al., 2011b). This is due to genetic influences coming from multiple genes and the gene pool changing too slowly to cause the observed increases (Egger & Swinburn, 1997). However, gene-environment and gene-behaviour interactions could play a role, particularly when mediated by epigenetic modifications (Burgio et al., 2015; Swinburn et al., 2011b).

Epigenetics is the study of potentially heritable changes that may affect gene expression through DNA methylation (Buchen, 2010). Epigenetics is an emerging field of study and understandings of its impact on obesity are still limited. There is evidence that maternal diet and circumstances influences DNA methylation as well, for example increased obesity rates were observed in some children conceived under famine conditions that persisted throughout life (Ahmed, 2010; Stein et al., 2007). This does not occur under all circumstances and may be more a matter of a mismatch between foetal conditions and experiences throughout life (Burgio et al., 2015). There is also some evidence that these epigenetic changes may be passed on to later offspring, as the grandchildren of those conceived under famine conditions may also exhibit higher body weights (Veenendaal et al., 2013). Thus, the experiences of an individual's mother and ancestors may affect their present-day weight.

Social conditions can influence body weight as well, and stress is a substantial contributor. Moore and Cunningham (2012) identify the hypothesised mechanisms for this relationship as operating through both biological changes (elevated cortisol and visceral fat deposition), and behavioural changes that increase caloric intake. This is backed up by evidence that stress, and stress eating, are associated with higher BMI (Laitinen, Ek, & Sovio, 2002; Moore & Cunningham, 2012). As these papers discuss, higher SES is often associated with lower stress levels, and thus this represents a substantial health inequity operating along a social gradient. This issue also connects to discussions around housing (Cheer, Kearns, & Murphy, 2002; Kearns, Smith, & Abbott, 1992), provision of social welfare (Baker, 2002; O'Brien, 2013), precarious work (Hannif & Lamm, 2005; Quinlan, Mayhew, & Bohle, 2001), and other social issues that may contribute to stress.

It is not merely low SES that impacts on obesity. Evidence suggests that more unequal countries have higher obesity rates, among developed nations adjusted for gross national income (Pickett, Kelly, Brunner, Lobstein, & Wilkinson, 2005). Similarly, countries with lower income inequality and a greater degree of market regulation had lower mean BMI (Egger, Swinburn, & Islam, 2012). These relationships also apply to other aspects of health. The main argument put forth to explain these relationships is that increased income inequality lowers social cohesion, and contributes to increased stress (Kawachi & Kennedy, 1997; Wilkinson & Pickett, 2006), and that these can be linked to the structural environment and neoliberal political ideology (Coburn, 2000).

Another mechanism through which social conditions may influence obesity is inequitable access to healthy foods (Drewnowski, 2009). Though evidence for whether access to food outlets has an impact on diet is limited, particularly outside of the USA, factors like price may still have an impact (White, 2007). Considerable concern has been raised by US and UK researchers about ‘food deserts’ — areas with low access to retail food outlets (e.g. Alwitt & Donley, 1997; Chung & Myers, 1999; Clarke, Eyre, & Guy, 2002; Walker, Keane, & Burke, 2010; White, 2007). Note that measuring and investigating access to food outlets in this way has been critiqued by other authors who argue that they frequently fail to capture non-traditional food outlet options, ignore cultural acceptability, and pathologise neighbourhoods and residents (Odoms-Young, Zenk, & Mason, 2009; Shannon, 2014).

In Aotearoa New Zealand, evidence about food deserts is mixed. Both Pearce, Day, and Witten (2008a) and Sushil, Vandevijvere, Exeter, and Swinburn (2017) demonstrated that access to all types of outlets — whether healthy or unhealthy — was better in more deprived neighbourhoods. Thus the concern is more likely to be ‘food swamps’ — areas with a much higher proportion of unhealthy food outlets than healthy outlets — which are more common in areas of higher deprivation (Sushil et al., 2017; Woodham, 2009). In particular, there is concern about spatial clustering of unhealthy food outlets around schools that is more pronounced in areas of higher deprivation (Day & Pearce, 2011). These complex interrelationships highlight the geographic complexity of the problem and will be discussed in more detail in Sub-section 2.3.3.

Intestinal microbiota play an important role in the digestion of food, and thus may influence body weight as well. There are differences in the species composition of intestinal flora in obese and non-obese individuals (Ley et al., 2006). Additionally, there are some indications that sudden weight changes after faecal microbiota transplantation are possible in humans — with more definitive evidence coming from animal models (Alang & Kelly, 2015; Bäckhed et al., 2004; Ley et al., 2006). The composition of an individual’s intestinal microbiota is influenced by their diet, which may interact with the stress based eating discussed above (David et al., 2014).

What individuals eat is also important from an obesity perspective. Different types of food are metabolised differently by the body and impact on weight gain to varying degrees, sugars have been particularly criticised in this respect (Bray & Popkin, 2014; Wells, 2013). Additionally, Tanumihardjo et al. (2007) discusses the relationship between obesity and nutritional status — beyond simple energy intake. They argue that high BMI is not necessarily an indicator that all nutrient needs are being met, and open the possibility of being both obese and nutritionally deficient (Gillis & Gillis, 2005; Kaidar-Person, Person, Szomstein, & Rosenthal, 2008; Tanumihardjo et al., 2007). Consuming highly processed foods is associated with higher body weight; these types of foods are often energy dense, highly palatable, low in essential nutrients, and produced for minimal cost (Monteiro, Moubarac, Cannon, Ng, & Popkin, 2013).

Two recent reviews reached conflicting conclusions on the subject of whether or not additional dietary sugar causes weight gain and metabolic disease. Bray and Popkin (2014) argued that sugar does influence health outcomes, and that consumption of sugary beverages in particular should be reduced. In the counter-point article, Kahn and Sievenpiper (2014, p. 957) assert that “there is no clear or convincing evidence” that sugar consumption has any detrimental impact on health relative to other sources. As with a similar point-counterpoint series discussed previously (Sub-section 2.2.1), the authors of the latter article declare funding sources that include The Coca-Cola Company among others.

Biases related to funding source is a potential issue raised by Stanhope (2016) while building on these reviews. She explains both the direct and indirect mechanisms through which sugars containing fructose can influence health as well as addressing the current evidence base on this topic. Her conclusion is that though the evidence for a link between sugar and metabolic disease is strongly suggestive, including plausible metabolic mechanisms for the action of sugar on the body, the evidence is not definitive. Essentially, though there is substantial evidence, the methodologies used in the existing literature allow vested interests to introduce doubt. Only studies designed with a randomised controlled trial methodology could provide sufficient evidence to prove a link definitively; this type of study is extremely difficult to obtain funding for (Stanhope, 2016).

2.2.3 Fat bodies and public health

Obesity's long association with 'gluttony or sloth' makes a connection between obesity and morality a common sense one for many (Evans, 2006, p. 259). This includes medical professionals (Ogden et al., 2001; Puhl & Brownell, 2001; Schwartz, Chambliss, Brownell, Blair, & Billington, 2003). In this view, every individual is at constant risk of becoming obese through eating the wrong foods or failing to exercise enough (van Amsterdam, 2013). This risk is framed as the result of inaction or complacency, rather than direct action, in contrast to smoking, and positioning obesity as a moral failing (Campos et al., 2005; Evans, 2006; Evans & Colls, 2009; Kwan, 2009; Saguy & Riley, 2005).

There is a considerable body of critical health research exploring critiques of BMI, the obesogenic environment and many other public health perspectives on obesity. Key criticisms include (with examples): that the link between obesity and health is not clearly established (Gard & Wright, 2001; Kirkland, 2011), that obesity is aligned as amoral (Evans, 2006; Gard & Wright, 2001; Warbrick et al., 2016), excessive focus on body weight can encourage eating or body image disorders — regardless of the body size of the individual (van Amsterdam, 2013), that a medicalised view of obesity frames fat[7] bodies as 'deviant' and diseased (Evans, 2006; Evans & Colls, 2009; Guthman & DuPuis, 2006; van Amsterdam, 2013), that the limitations of BMI frame the results that are obtained (Colls & Evans, 2014), that the debate readily strays into biological or environmental determinism[8] (Colls & Evans, 2014; Parr, 2002). Additionally critical research draws attention to the stigma and discrimination associated with obesity — and the unequal distribution of this stigma (Colls & Evans, 2014; Evans, 2006; Evans, Davies, & Rich, 2008; Fikkan & Rothblum, 2012; van Amsterdam, 2013).

Though different groups may disagree about the risk excess body fat poses to wellbeing, critical health researchers do make important points that are worth considering. The critical literature challenges conventional notions of good health by pointing out that obesity is not necessarily synonymous with sickness, and nor does thinness guarantee health — not even when considering NIDDM, a disease considered to be strongly related to obesity (Evans,

[7] In this section and several others, the term 'fat' is used to describe bodies as the term 'obese' is disputed in the literature under discussion due to its medicalisation of body size (Colls & Evans, 2014).
[8] Essentially, environmental determinism in this context is the implication that living in a particular type of environment will necessarily result in an individual becoming fat, something that ignores individual choices and is clearly untrue.

2006; Kirkland, 2011). Further, critiques draw attention to the stigma associated with fatness, and challenge that stigma (Evans et al., 2008). Critically, these researchers remind us that the health care sector contributes to the negative impacts of obesity through the stigmatisation of fat bodies (Campos et al., 2005; Colls & Evans, 2014; Evans, 2006); inadequate medical care often received by fat patients (Puhl & Brownell, 2001); and the ongoing assumption that individuals have full control over their weight despite mounting evidence that many of the causes are outside of individual control (see Section 2.3, and Sub-sections 2.2.1, and 2.2.2).

Policy makers have a difficult task in balancing individual agency[9] and avoiding victim blaming (Adler & Stewart, 2009). On the one hand, if an individual has control over their body weight then they are to be considered responsible if it is too high; a problematic stance given the limited control individuals have. On the other hand, if the individual has no control over their body weight, they become a helpless victim of the environment around them; thus depriving the individual of any agency. Thus it is necessary to walk a middle ground between these extremes (Adler & Stewart, 2009; Brownell et al., 2010).

The view of obesity presented in this thesis will be a BMI-centric one because that is the data available, and that is the accepted standard in Aotearoa New Zealand. However, it is important to acknowledge that this has the potential to perpetuate all of the problematic and medicalised attitudes to obesity that are described here. In order to counteract this, the Discussion (Section 7.2) will return to the critiques that have been described here.

2.2.4 From individual to environment: Politics, population, and policy

The risks of obesity are contested among different groups of researchers and stakeholders (Evans, 2006; Gard & Wright, 2001; Swinburn et al., 1997; World Health Organisation, 2000). Obesity may cause excess morbidity or mortality, or it may not (Evans, 2006). Obesity may be a symptom of other medical conditions or social ills, or it may not — depending on the individual (Després & Lemieux, 2006; Evans, 2006). The stigma associated with excess body weight and the negative effects of that stigma are not in question, though how fat one needs to be to experience it and which groups are most affected may be (Puhl & Heuer, 2010). Regardless, until alarm about the obesity epidemic developed in recent decades,

[9] Agency refers to the choices individuals make — influenced by both past and future. It stands in contrast to structure — all of the things outside of the individual that influence their decision making and which may shape or restrict their choices. For a deeper discussion see Abel and Frohlich (2012) and Cockerham (2005).

obesity was uncommon and malnutrition was a greater concern (Caballero, 2007). The rise in obesity rates to around one third of the population presents difficulties to the public health system, social difficulties to the individual, and most likely medical difficulties as well — whether they are caused by excess body fat or not. This is a problem that cannot be ignored, regardless of its causes or its framing.

Obesity is widely acknowledged as a complex — or ‘wicked’ — problem one with many causes and no simple solution (Butland et al., 2007; Finegood, Merth, & Rutter, 2010; Signal et al., 2013; Swinburn et al., 2011b). Evidence for any single intervention is often ambiguous because no one factor alone is enough to have a substantial effect, thus policy making can be a complex process. There are two main frames used by different interest groups in Aotearoa New Zealand — the first is personal responsibility, and the second the obesogenic environment (Jenkin et al., 2011). There is a ‘medical’ frame related to the public health frame, which focuses more on treatment (Adler & Stewart, 2009; Kwan, 2009). The fat acceptance frame described by Kwan (2009) appears to be largely absent in Aotearoa New Zealand (Jenkin et al., 2011), despite some attention from local researchers (Longhurst, 2005).

The frame of personal responsibility is used by industry to excuse action and avoid regulation, placing blame onto the individual. The main defence against regulation that has been mounted by the food and beverage industry revolves around the personal responsibility of the individual for their own health and objections to ‘nanny state’ interventions into personal freedoms (Brownell et al., 2010; Kersh, 2015). Personal freedom was also the rallying cry of the tobacco industry when first facing regulation (Brownell et al., 2010). However, Brownell et al. (2010) argue that personal responsibility can be used constructively — when framed correctly and placed in the right environment through appropriate policy actions. They identify key policies for creating healthier environments that better enable individuals to make healthier choices, these include: regulating food marketing (particularly to children), school food environments, food labelling, regulation of ingredients, and taxes.

The frame of the obesogenic environment is primarily used by the public health sector. This frame reflects a body of knowledge that has grown over the past 20 years: that the environment impacts on body weight in many subtle ways many beyond the capacity of an individual to influence on their own (Egger & Swinburn, 1997; Kirk, Penney, & McHugh, 2010; Smith, Edwards, Clarke, & Harland, 2010). The range of environments that may influence obesity is very broad, encompassing physical, sociocultural, economic and political environments, and operates at a variety of scales (Swinburn, Egger, & Raza, 1999a). It is these environmental influences that make obesity such a complex problem. Over reliance on this frame can easily become environmental determinism, and remove individual agency (Adler & Stewart, 2009; Colls & Evans, 2014).

Neither of the two extremes is helpful, either to individuals or policy development. On the one hand, to say that individuals are solely responsible for their own weight ignores the wide range of circumstances outside of individual control that impact on body weight. And on the other, to say that individuals have no impact on their body weight and are merely victims of an obesogenic environment ignores the impact that individual choice does have, and robs the individual of any agency over their health status. There is a need to carefully navigate competing viewpoints in order to achieve improvements in health outcomes (Adler & Stewart, 2009). Brownell et al. (2010) argue that it is politically easier to achieve regulation when it is framed within existing norms — like personal responsibility — and this may be an important tool for policy makers facing political inaction.

2.3 Differing explanations

The previous section established that there are several competing explanations for the causes of obesity, as well as some of the challenges of defining what obesity is. The objective in this section is to outline some of the common frames used by different groups to understand and explain obesity before discussing the concept of obesogenic environments in more detail. The obesogenic environment concept is useful for exploring obesity from a geographic perspective as it explicitly includes consideration of the impacts of the built, social, economic, and other environments in which individuals live.

This section of the literature review will be structured as follows: Sub-section 2.3.1 opens the section by describing some of the common frames used to discuss obesity. Sub-section 2.3.2 follows this with a discussion of obesogenic environments specifically. Next, built environments (Sub-section 2.3.3) and social and economic environments (Sub-section 2.3.4) are discussed in greater detail. Finally, Sub-section 2.3.5 addresses critiques of the obesogenic environment.

2.3.1 Framing obesity

Different groups frame the obesity epidemic in different ways depending on their perspective. These frames can be very different and sometimes incompatible, and even different sources from within a single frame may give contradictory positions (see Table 2.2). In the extreme, obese individuals can be framed as ‘helpless victims’ (public health), ‘lazy over eaters’ (industry), ‘sick’ and in need of treatment (medical), or not related to health at all (health at every size, HAES).

Table 2.2: Frames used by different stakeholder groups to describe obesity.

Group	Perspective	Reference
Medical	UK — Obesity is a risk to health. It is primarily caused by overeating. It is the responsibility of the individual to make lifestyle changes.	Ogden et al. (2001)
	US — Obesity is an epidemic which has high costs (medical, social, and economic). The causes of obesity are highly complex. Remedies require both government and individual action, as well as more research.	Kwan (2009)
Patients	UK — Obesity makes life more difficult. It is most likely to be caused by something beyond the patient's control (a medical problem, slow metabolism, or stress). It is the responsibility of medical professionals to provide intervention.	Ogden et al. (2001)
Public Health	NZ — Obesity is a normal consequence of an obesogenic environment. It is primarily caused by the promotion of and easy access to cheap, high calorie, nutrient poor food, but social inequities play a role. It is the responsibility of government to regulate industry and promote better health outcomes.	Jenkin et al. (2011)
Industry	NZ — Obesity is a problem of poor lifestyle choices. It is primarily caused by lack of physical activity. It is the responsibility of the individual to make informed and healthy choices, government should only attempt to educate consumers and not otherwise interfere.	Jenkin et al. (2011)
	US — Obesity is not a disease. It is caused by lack of physical activity, food and drink does not cause obesity alone. BMI is a misleading indicator of health. It is the responsibility of individuals to make their own 'common sense' choices, government should not interfere.	Kwan (2009)
Health at Every Size (HAES)	US — Fat is stigmatised due to social conceptions of beauty, narrow medical definitions of health, and inappropriate use of BMI. There are multiple causes, which can include dieting history. It is important to address size based discrimination and redefine health without reference to body size.	Kwan (2009)

None of these positions are helpful on their own. The industry and medical perspectives engage in victim blaming, the public health perspective renders individuals as ‘helpless victims’ of an obesogenic environment, the patient perspective is self-serving — it is neither their fault nor their responsibility to fix it, and the HAES perspective does not adequately recognise the real negative effects of obesity. However, it is important to identify these perspectives in order to understand the underlying paradigms of different actors within this field.

The perspective utilised in this thesis is closest to the public health perspective outlined above, with the addition of some aspects of the HAES and second medical perspective (from Kwan, 2009). This perspective recognises the complex interaction of many factors places heavy weight on structural and environmental causes: food environments, socio-economic status, stress, cultural influences, built environment, etc. However, it also recognises the importance of maintaining individual agency (Adler & Stewart, 2009; Brownell et al., 2010), as well as addressing the stigmatisation of obesity (Puhl & Heuer, 2010).

2.3.2 Overview of obesogenic environments

The environment, as it pertains to obesity, is complex and multifaceted. There are many causal factors, many mediating factors, and effective responses to obesity must be complex as well. From a spatial perspective, much of the research done on obesity has concentrated on the ‘obesogenic environment’ (Egger & Swinburn, 1997); in other words, the physical and social environments in which people live that promote obesity. The concept encompasses almost anything that could promote obesity from the micro scale of individual choices to the macro scale of government policy and international relations. Factors that may make an environment obesogenic include, but are not limited to: the food environment (regulation, taxation, availability, attitudes, choice, costs), practicality of active transport such as walking or cycling (safety, street connectivity, green space), household income (food security, stress), and access to recreational facilities (e.g. Egger & Swinburn, 1997; Signal et al., 2013; Swinburn et al., 1999a). These factors and an individual’s behavioural and physiological response towards them may vary by sex, age, ethnicity or other factors; however, they are important predictors of obesity (Egger & Swinburn, 1997; Swinburn et al., 1999a).

Even more importantly from the perspective of this research, obesogenic factors have heterogeneous spatial prevalence (Pearce & Witten, 2010a). This heterogeneity of distribution will necessarily impact on the distribution of obesity both within the population and across space. Populations may benefit from interventions tailored to the specific needs of each small area (Edwards, Clarke, Ransley, & Cade, 2009). Thus, considering both the physical and social environments together in order to examine small area distribution of obesity within the population is important; several examples can be found in Pearce and Witten (2010b).

Research on obesogenic environments can be technically difficult as survey and other data forms are usually connected with a small area corresponding to the participants' home location. This is not necessarily well correlated with their exposure due to edge effects and daily movements to work and leisure activities (Burgoine & Monsivais, 2013). Additionally, just as education does not necessarily result in behaviour change (Michie, van Stralen, & West, 2011; Thompson & Kumar, 2011), availability does not necessarily result in consumption (Jeffery, Baxter, McGuire, & Linde, 2006). An individual living next to a park or fast food outlet may never use that facility, it may be culturally inappropriate, unsafe, or not available at a convenient time (e.g. Molnar, Gortmaker, Bull, & Buka, 2004; Odoms-Young et al., 2009). However, geographic research commonly uses home location is commonly used as a proxy for exposure in the absence of better alternatives.

Overall, the obesogenic environment creates a complex system within which individuals are sited. Each individual responds to this environment, and makes choices about their health, differently (Cockerham, 2005).

2.3.3 Built environments

The physical or built environment is one aspect of obesogenic environments that are commonly investigated by geographers. Research on how these types of environments impact on obesity tend to concentrate on the ability of the environment to promote or inhibit physical activity or food, i.e. the parts of the energy balance model that appear to be amenable[10]. Topics of interest have centred on greenspace, walkability (and related issues), and food outlets (both healthy and unhealthy), and access to neighbourhood resources, as well as different geographic scales (Smith & Cummins, 2009). There have also been attempts at building ecological models of obesity (Sallis, Floyd, Rodríguez, & Saelens, 2012) and other similar methods of analysis (Swinburn et al., 1999a).

[10] Though whether physical activity influences risk of obesity is a matter of contention (Luke & Cooper, 2013b).

The impacts of the built environment on obesity have been the subject of a considerable amount of research, with a number of different reviews published in the last decade examining different aspects of obesogenic environments. Many studies examined by these reviews show a link between the built environment and obesity outcomes, but some studies show no effect or the reverse effect to what was expected (Booth, Pinkston, & Poston, 2005; Feng, Glass, Curriero, Stewart, & Schwartz, 2010; Fleischhacker, Evenson, Rodriguez, & Ammerman, 2011; Lachowycz & Jones, 2011; Papas et al., 2007). A wide variety of methods are employed across the body of published literature and this is a likely cause of the variation in observed results; it also limits the ability to make comparisons between studies (Booth et al., 2005; Feng et al., 2010; Papas et al., 2007). Additionally, Kirk et al. (2010) identified that there is a lack of research relating to obesogenic environments at a macro scale (city or larger) or with respect to the political environment. Environmental factors at this scale affect large population groups and are important to understanding how the environment impacts on obesity.

International research suggests that open space and street connectivity increase physical activity, but there is a lack of specific research on lower SES populations and it is unclear if these findings hold true among those groups (Pearce & Maddison, 2011). This echoes Rosenberg's (2016, p. 2) concern that *"…the findings from such studies are being used to argue for changes in the built environment when the studies so clearly represent the values of the better educated, those with the most time to walk and use recreational spaces…"*. There is a Aotearoa New Zealand based project called Te Ara Mua which is investigating urban design improvements in a low SES area which may begin to fill in some of these gaps (Auckland Transport, 2017; Te Ara Mua, 2017), but the outputs have not yet been published in a peer reviewed format. The outcomes of this project will expand current knowledge of the impacts of the built environment on a lower SES population in Aotearoa New Zealand.

Research on obesogenic environments in Aotearoa New Zealand has shown that in urban environments, deprived areas often have better access to neighbourhood resources that promote physical activity. Assessing a broad range of destinations in urban areas using a GIS tool called the Neighbourhood Destination Accessibility Index (NDAI), Witten et al. (2011) found considerable variation in accessibility among different locations and at different scales but with a broad trend to greater access in more deprived places; this is contrary to what is often observed in the USA. Associations between better neighbourhood characteristics, such as access to destinations (NDAI), street connectivity, density, and higher levels of physical activity (e.g. Witten et al., 2012) would imply that those living in more deprived areas may have higher levels of physical activity. However, neighbourhood characteristics do not act in isolation, and there is also evidence that personal characteristics such as access to a car modify the impacts of neighbourhood characteristics on physical activity (Ivory et al., 2015).

The observed relationship between deprivation and access to neighbourhood resources does not hold across all kinds of environments. Associations like those described above, between deprivation and access to community resources such as GPs, supermarkets, or greenspace, are predominantly found in urban areas (Pearce, Witten, Hiscock, & Blakely, 2007b, 2008b). Though the pattern of better access in deprived areas holds true in some rural locations, in others higher deprivation is associated with a lack of access to community resources; there was also evidence of regional variation in this effect (Pearce et al., 2008b).

Similarly, access to unhealthy food outlets such as convenience stores, fast food, and alcohol outlets is better in urban deprived areas in both Aotearoa New Zealand and the UK (Fraser, Edwards, Tomintz, Clarke, & Hill, 2012; Pearce, Blakely, Witten, & Bartie, 2007a; Pearce et al., 2008a). This pattern is also evident in the food environment around schools with unhealthy food outlets clustered around schools, particularly in low SES areas (Day & Pearce, 2011; Vandevijvere, Sushil, Exeter, & Swinburn, 2016; Walton, Pearce, & Day, 2009). In one Aotearoa New Zealand study, there was no association between areas with good access to fast food outlets and overweight or consumption of fruit and vegetables, areas distant from multinational fast-food outlets were more likely to meet daily fruit and vegetable intake recommendations and be overweight (Pearce, Hiscock, Blakely, & Witten, 2009). A UK study demonstrated that although access to fast food outlets was higher in more deprived areas, access was negatively associated with obesity (Fraser et al., 2012). Thus, the home environment is by no means guaranteed to provide a good estimate of real exposure to an individual (Shearer et al., 2015).

Access to resources does not guarantee that those resources will improve health outcomes in general, or obesity in particular. Richardson, Pearce, Mitchell, and Kingham (2013) found that though greener neighbourhoods had better health outcomes, this did not translate to lower obesity risk. Conversely, Pearson, Bentham, Day, and Kingham (2014) found that access to greenspace decreased the risk of obesity. These two studies were measuring different things and so are not necessarily contradictory, but this does illustrate the difficulty of understanding obesity-environment interactions.

2.3.4 *Social and economic environments*

Social and economic environments encompass everything else that can impact on body weight and obesity, from social stigma to the cost of food. These factors act at all scales to influence the environment in which individuals make decisions, from interactions between two people to national government policy and international economic conditions. Key social and economic issues include culture and ethnicity, socio-economic status, cost of living, food security, income inequality, and political issues. Governments are commonly interested in creating measures that capture these factors, such as the New Zealand Deprivation Index, NZDep, a composite index comprising nine indicators (Atkinson, Salmond, & Crampton, 2014). However, single variable measures do a poor job of capturing the complexity and multiple domains of socio-economic deprivation, and deprivation indices in general risk privileging euro-centric middle-class norms (Exeter, Zhao, Crengle, Lee, & Browne, 2017; Fu, Exeter, & Anderson, 2015b).

In developed countries like Aotearoa New Zealand, lower SES is associated with larger body size (McLaren, 2007; Sobal & Stunkard, 1989). This is certainly borne out by recent NZHS data, with the majority of recent increases in obesity rates being driven by increasing obesity in more deprived areas (Ministry of Health, 2016a). The NZHS also showed that those living in the most deprived areas have obesity rates 70% higher than those living in the least deprived areas. There is some debate around whether the effects of deprivation are contextual (neighbourhood factors) or compositional (individual factors); in other words are the effects inherent to an individual's situation or the place in which they have chosen to live? (Gaskin et al., 2014; Ross & Mirowsky, 2008). Low SES in Aotearoa New Zealand is very strongly associated with Māori and Pacific ethnicities. This complicates current understandings of obesity in Aotearoa New Zealand, because as explained earlier (Sub-section 2.1.4) Māori and Pacific individuals will exhibit *higher* BMI at the same percentage of body fat than a European individual.

One of the major connections between SES and obesity is stress. As discussed earlier (Sub-section 2.2.2), Moore and Cunningham (2012) demonstrated that high SES is associated with lower levels of stress, better diet, and lower body weight; and also that higher levels of stress were associated with less healthy eating and higher body weight. By implication then, low SES is associated with higher stress, as well as poorer diet and higher body weight. The hypothesised pathway they used to illustrate these relationships included both behavioural and biological changes in response to stress.

Much of the language around obesity, particularly the language of personal responsibility for diet and exercise, frames excess body weight as a personal failure. Thus those with bodies which do not conform to perceived norms are judged as amoral and stigmatised, whereas those who are perceived to be healthy are judged to be ‘morally worthy’ (Evans, 2006; LeBesco, 2011). Arguments for personal responsibility can be used constructively in the right environment, but generally are not (Brownell et al., 2010).

The effects of obesity related discrimination can cause additional harm. Discrimination concerns associated with obesity include issues around employment, health care, psychological distress, among others (Puhl & Heuer, 2009; Puhl & Heuer, 2010). One study demonstrated that less obese individuals who experienced weight discrimination had worse outcomes than those who were more severely obese but did not experience weight discrimination (Schafer & Ferraro, 2011). Even very high status — such as holding a top business executive position — may be insufficient to overcome the stigma associated with obesity (King et al., 2014). Other forms of discrimination can also be harmful: there is some evidence of a link between lesbian, gay, and bisexual youth of minority ethnicity and obesity, likely due to stress resulting from discrimination (Austin, Nelson, Birkett, Calzo, & Everett, 2013).

A considerable amount of research has gone into assessing whether cultural factors may influence obesity rates. An investigation into Pacific Peoples’ attitudes towards body size conducted by a researcher of Pacific ethnicity found no evidence of a preference for unhealthy body size (Teevale, 2011). The same researcher demonstrated that Pacific school students purchase (generally unhealthy) school lunches more frequently than other ethnic groups (Teevale, Scragg, Faeamani, & Utter, 2012). This research identified that parents saw purchased lunches as convenient given time constraints, a way of valuing their child’s independence, and as a way of compensating children for poverty and lack of other resources. Concerningly, obesity rates among the Pacific population in Aotearoa New Zealand are very high, with almost all of the older Pacific adults (age 35 – 74) in one study being overweight or obese, requiring whole-of-population change (Sundborn et al., 2010).

In some population groups, lack of food security may influence obesity rates. Lower cost foods are often less healthy but more can be purchased when money is limited (Rush, Puniani, Snowling, & Paterson, 2007). The definition of food insecurity comprises not only the quantity of the food available in a household, but also its quality and the uncertainty of food supply (Alaimo, Briefel, Frongillo Jr, & Olson, 1998). Food insecurity is influenced by a complex array of factors, including access to a home garden, transportation, and food preparation skills, not merely income and financial factors alone (Gorton, Bullen, & Mhurchu, 2010). However, longitudinal studies indicate that though those on low incomes have higher levels of obesity, when resources are constrained — such as during the 2008 Global Financial Crisis — BMI does decrease or increase at a lower rate (Hruschka, 2012).

Food security in Pacific families is particularly poor. Nearly 40% of families with young children in one study ran out of food sometimes, and variety of foods was limited by lack of money in 39% of participating families (Rush et al., 2007). Food insecure households spend less on important food groups than households with higher food security (Smith, Parnell, Brown, & Gray, 2013). Further complicating the issue of food security is that healthy foods are more expensive than 'regular' options in both urban and rural areas in Aotearoa New Zealand (Wang et al., 2010).

There is also evidence of a gender component to the issue of food security. Evidence from the USA shows that some single mothers may compromise their own diet in order to ensure that their children have adequate food during times of shortage, and this contributes to a higher risk of overweight and obesity in this group (Martin & Lippert, 2012). Food insecurity is higher in women than men in Aotearoa New Zealand, with one study finding that 11% of males and 16% of females indicated that food runs out in their household due to lack of money (Parnell, Reid, Wilson, McKenzie, & Russell, 2001).

Housing can impact on obesity rates in a variety of ways. Location and density of housing has implications for transportation costs, level of physical activity and obesity; and additionally, quality of housing can impact on health more broadly (Howden-Chapman & Chapman, 2012). Additionally the cost and quality of housing has impacts on the household budget, if the house is expensive to heat it may have implications for the household food budget (Frank et al., 2006; Howden-Chapman & Chapman, 2012; Rydin et al., 2012).

There is an increasing body of evidence about what kinds of interventions work to reduce obesity, including a number of successful programmes from Aotearoa New Zealand; however, there is no guarantee that a successful pilot program will go on to become government policy. Theodore et al. (2015) describe a series of events where multiple studies identified effective interventions that reduced obesity in participants but were not continued after the end of the study period. One of these, Healthy Eating — Healthy Action (HEHA) which incorporated the principles of Treaty of Waitangi, was discontinued after a change in government along with several associated programs and policies (Swinburn & Wood, 2013). The policy which replaced HEHA relied more heavily on educating individuals, this type of strategy is known to not only be less effective at combating obesity, but may also increase socioeconomic inequities in obesity rates (Backholer et al., 2014; Theodore et al., 2015; Thompson & Kumar, 2011).

The challenge for policy makers is no longer identifying what policies will work, it is persuading politicians to make unpalatable choices. A review of the New Zealand Government's nutrition policy found that it was more closely aligned with industry interests than public health outcomes, and the only exception to this was later reversed by a change in government (Jenkin, Signal, & Thomson, 2012). Many policies that would contribute to healthier environments (e.g. targeted taxes, food labelling, restricting marketing, or restricting the types of food available in schools) are unpalatable to industry which continues to argue for personal freedom from government intrusion; and these arguments do have an influence on government policy (Brownell et al., 2009; Brownell et al., 2010; Jenkin et al., 2012).

2.3.5 Critique of the obesogenic environment

Critiques of the obesogenic environment often focus on the implicit assumptions made about what it is to be healthy and how the environment impacts on health. This may include challenging the connection between obesity and health, implicit assumptions about morality, or the agency of the individual and environmental determinism. In particular, critiques highlight the need to reconceptualise the concept of the obesogenic environment in a way that does not make assumptions about what a healthy body or a neighbourhood is (Colls & Evans, 2014). The difficulty of achieving sustained weight loss in adults is a further complication (Aphramor, 2010).

Critical geographies of obesity challenge the assumption that obesity and (ill-)health are synonymous, arguing that obesity is better described as a symptom rather than a cause of ill-health (Campos et al., 2005; Evans, 2006; Evans & Colls, 2009). Evans and Colls (2009) posit that although obesity is described as a disease, it is one without any experienced ill-health where the body is diagnosed through population based classification tables. Ross (2005) further explains this by noting that the WHO definition of obesity as a disease (World

Health Organisation, 2000) rests on obesity's contribution to ill-health, rather than being itself a state of ill-health. This mismatch is illustrated by studies that show improved outcomes related to physical health (e.g. cholesterol, amount of exercise) independently of weight loss (Aphramor, 2010). However, it is important to note that there is a great deal of contention on this subject; one study demonstrated that metabolically normal obese individuals experience higher risks for CVD (Caleyachetty et al., 2017), and another that overweight (BMI 25 to 29.9) had a protective effect against mortality (Flegal et al., 2005).

Another criticism of the obesogenic environment surrounds how a healthy environment is defined. Despite the best intentions of health geographers and public health researchers to avoid blaming the victim, much of this work unintentionally promotes implicit assumptions about morality by promoting euro-centric, middle-class norms as the healthiest option (Colls & Evans, 2014; Kirkland, 2011; Shannon, 2014). Kirkland (2011) cites as an example that the sugar in honey is considered healthy while white table sugar is not, and similarly priority is given to fresh fruit and vegetables, when frozen or canned (assuming no added sugar) is comparably healthy and most likely cheaper. Other examples are cited in Colls and Evans (2014) and Kirkland (2011), such as the use of tenure as a measure of social cohesion, measuring aesthetic attributes through graffiti or maintenance of green spaces, the identification of cultural foods or practices as 'unhealthy', or the use of 'hours worked by mothers' as a proxy for unhealthy lifestyles. Indeed, Odoms-Young et al. (2009) question the extent to which obesogenic environments research is representative of communities of colour, and identifies alternative methods, as does Raja, Ma, and Yadav (2008). Colls and Evans (2014) also highlight how this may be a self-fulfilling cycle whereby the stigmatisation of obese individuals may keep them obese through the stress caused by stigmatisation (see also Sub-section 2.3.4).

Colls and Evans (2014) specifically critique microsimulation models, arguing that these and other types of positivist research on obesogenic environments often fail to acknowledge the problems with using BMI, and that these issues may be magnified by the use of age, gender, and ethnicity to build the model. Sub-section 2.1.4 of this thesis acknowledges some of the issues with using BMI in this research, particularly using a single categorisation of obesity cut offs. As BMI is the accepted statistical and methodological standard for the measurement of obesity in Aotearoa New Zealand (Ministry of Health, 2008a, 2014c), it is difficult to choose to deviate from it. This thesis also argues that the benefits of understanding more about neighbourhood level obesity in Aotearoa New Zealand, outweigh the drawbacks of using BMI as a metric; Section 7.2 will return to this topic.

Within an Aotearoa New Zealand context, Warbrick et al. (2016) argue that the individualised neoliberal model of health, and strong focus on obesity and body weight are at odds with Māori models of health. The key difference in approach is that Māori models of health situate the individual within the environment in which they live and address the whole picture not the individual alone — a contextual approach that can be beneficial to all regardless of ethnicity (Warbrick et al., 2016), see later discussion in Section 3.3. The way in which SMSM disrupts people-place connections could be potentially problematic from a Māori perspective, underscoring the need to utilise the SimAotearoa model as a tool and an indicator, not an absolute measure of health for small areas.

These critiques suggest that it is important that the obesity related results presented later in this thesis should be viewed as describing a symptom of ill-health, rather than monitoring a disease. It also suggests that estimates of diagnosed diseases (e.g. NIDDM), or behaviours more closely associated with health (e.g. diet and physical activity) may be more useful than obesity estimates themselves. A holistic view of health is critical to understanding both obesity and the results presented in this thesis. It is important to remember that the environment does not directly dictate either outcomes or individual choices. The environment shapes the choices available to the individual, but is made by circumstances outside of their control; it may restrict or enhance the choices made by individuals but does not directly determine them (Cockerham, 2005).

2.4 Spatial microsimulation and health

The previous section addressed a variety of different perspectives and explanations for obesity. It concentrated on the obesogenic environment as a geographic paradigm for understanding obesity. This section will establish a gap in the small area estimation of obesity rates that can be filled using SMSM and describe how SMSM can be used to analyse health issues and policy. In order to facilitate this, a brief introduction to SMSM is provided, so that the reader can understand the concepts discussed in Chapter 4.

This section is structured into six subsections. Sub-section 2.4.1 begins by establishing a gap in the literature around the scale and methods used to assess obesity at small area level. Sub-section 2.4.2 follows giving a brief overview of what SMSM is and some considerations for building a model. Sub-section 2.4.3 follows this introduction with a discussion of SMSM's use for policy analysis. Examples of published SMSM models used for health in general are provided in Sub-section 2.4.4, and for obesity specifically in Sub-section 2.4.5. Sub-section 2.4.6 concludes with an assessment of why the use of SMSM provides advantages over existing data sources.

2.4.1 Spatial variation in obesity

Studies of spatial variation in obesity rates have been limited, and few have incorporated consideration of the obesogenic environment. Most are concerned with variation among regions within a country or other large areas, such as whole cities; unlike analyses of the built environment described earlier (Sub-section 2.3.3), neighbourhoods are often too small to explore with small area estimates using conventional statistical methods. One example of large area spatial analysis is the regional analysis of the NZHS results (Ministry of Health, 2015d). Studies of this type also include variation by country, or international region. All the studies examined found some degree of spatial variation, though patterns vary depending on the country and scale.

Finucane et al. (2011) examined changes in BMI over time in various regions of the world using Bayesian methods in a meta-analysis. They found that BMI increased worldwide between 1980 and 2008, alarmingly so in some regions, but with substantial variation. The highest average BMIs identified in this study were in Oceania — a group of Pacific Island nations. Berghöfer et al. (2008) reviewed published articles on obesity in Europe and found substantial variation among nations with rates ranging from 6 to 36% in women, and from 4 to 28% in men. These types of studies do examine spatial variation in obesity rates, but at very large scales. They are important for understanding patterns of obesity among countries, but not useful for understanding finer-scale impacts on communities.

A sub-national regional scale was the most common way of investigating spatial variation in obesity rates. Studies reporting results at this scale used standard survey methods to generate estimates for states or regions including examples from the USA, England, Canada, Spain, and Aotearoa New Zealand (Ford, Mokdad, Giles, Galuska, & Serdula, 2005; Gutiérrez-Fisac et al., 2012; Le et al., 2014; Ministry of Health, 2015d; Vanasse, Demers, Hemiari, & Courteau, 2006). There was considerable variation in the exact obesity rates reported in different studies, as well as in the range of obesity rates reported — even within the same country. The lowest range of obesity rates (the difference between the highest and lowest rate) was 10%, reported in England (Moon, Quarendon, Barnard, Twigg, & Blyth, 2007), the highest rate, 42%, was reported in Canada (Vanasse et al., 2006). These types of studies are useful for understanding within-country variation, but still cover very large areas and are constrained by their methods. In addition, one study was located which examined diabetes in Auckland at electoral district level — a scale smaller than DHB but still large in comparison to a neighbourhood (Warin, Exeter, Zhao, Kenealy, & Wells, 2016).

A small number of studies have examined variation in obesity at a smaller scale such as postal code areas. This kind of study is much more difficult to execute due to the scarcity of data — it is necessary to have an adequate quantity of data points for every small area in the study — consequently they are relatively rare. In King County, Washington in the USA (Seattle) Drewnowski, Rehm, and Solet (2007) used Bayesian smoothing methods to investigate obesity. They found obesity rates that varied between 10 and 26% after smoothing, and that household income — a measure of SES — was a significant predictor of obesity prevalence. The range of estimated obesity rates was greater prior to smoothing. Another study used multilevel small area synthetic estimation to examine obesity at the scale of Primary Care Trusts in England (Moon et al., 2007). The obesity rates identified ranged from 14 to 22%, which seems somewhat incongruous when the same study reported that the Health Survey for England showed obesity rates up to 27% in some regions. These types of studies are much more useful for understanding obesity at a neighbourhood level, but still have methodological constraints as described above.

Though the majority of research into the geography obesity utilises administrative boundaries this is not essential. One unusual study from Finland used point data and Bayesian methods to generate obesity estimates in 10km by 10km grid cells (Lahti-Koski et al., 2008). However, in most countries (including Aotearoa New Zealand) it is impossible to obtain the data necessary to perform this kind of analysis for privacy reasons.

The methodological limitations on the scale of analysis of obesity rates are important. The modifiable areal unit problem indicates that when data are spatially clustered, very different results can be obtained depending on the scale of the areal unit and data included within it (Openshaw, 1984a). For example, an accurate obesity rate produced for a large area (such as a country), may obscure wide disparities in obesity rates among neighbourhoods. Even regional statistics may obscure substantial inequities. Consequently, information about obesity at a small scale is very valuable in order to detect and understand potential inequities.

Several studies examining obesity at a local scale have used SMSM to estimate obesity rates (e.g. Cataife, 2014; Edwards, Clarke, Thomas, & Forman, 2011; Koh, Grady, & Vojnovic, 2015). This method does not require data to be collected from every small area, meaning that it can be applied in more situations and to smaller areas. Further, SMSM does not rely on a small sample of people to accurately estimate obesity in a population that may be over 1000. This methodology will be discussed in the next section.

2.4.2 What is spatial microsimulation modelling?

Guy Orcutt (1957) is generally recognised as developing the first micro-analytic simulation for economic modelling, although the model did not have a spatial component. However, Hägerstrand (1967), investigated changes in the distribution of innovation and its diffusion through space. This work, originally published in 1953 (in Swedish) *before* Orcutt's (1957) seminal paper represents the first attempt to simulate spatial data in this kind of way. The first recognisably modern use of *spatial* microsimulation — that is modelling spatial data for households and individuals — originates in the 1970s with Wilson and Pownall (1976). Further discussion of this early work can be found in Ballas and Clarke (2009) and Birkin and Clarke (2011). *A*spatial microsimulation models are now commonly used for economic modelling, especially for tax and social policy simulation (Merz, 1991; O'Donoghue, Loughrey, & Morrissey, 2014) including an example from Aotearoa New Zealand (Smith & Euller, 1992). However, microsimulation is also used in a number of other fields including transportation, population, economics, and health (Ballas & Clarke, 2009). Spatial models are useful for examining not only the spatial distribution of a variable of interest, but also in examining spatial variation in the impacts of a national policy change (Ballas & Clarke, 2001).

SMSM is an analytical technique for generating detailed small area data where none are available through standard statistical methods. To do this, the SMSM combines small area data containing a small number of variables (generally census data) with a more detailed microdata set (generally a survey of some kind) containing a large number of variables but with no geography attached (Ballas, Clarke, Dorling, Rigby, & Wheeler, 2006; Hermes & Poulsen, 2012a). A number of different methodologies are available to do this, but all methods combine the two data sets using variables common to both (such as age, sex, ethnicity etc.) and produce a complete synthetic population for each small area in the study; these constraint variables must also be predictive of the variable of interest (Tanton, 2014). In other words, the model creates something that looks and acts like a census data set from the individuals in the microdata set.

The advantage of SMSM over census data is that the researcher has considerably more control than they would when accessing aggregated national census data. For example, in order to tabulate information for a particular sub-population the researcher may tell the model to extract data from that sub-population only; whereas when accessing census data, a researcher must hope that the right kind of data table is available, or make a specific request. This feature is of considerable benefit when assessing differential impacts by subgroup (Tanton, 2014).

When constructing a SMSM, many choices must be made. The most important question is in regards to the final output of the model: will this be a *static* model, capturing a population in space at a fixed point in time, or a *dynamic* model, reflecting longitudinal population changes over time? (Ballas et al., 2005c). Once this choice has been made, the details of how the model will be constructed must be addressed. Will the synthetic data set be created using *reweighting*, taking an existing microdata set and reweighting it to reflect a larger population, or *synthetic reconstruction*, where entirely synthetic individuals are created according to known distributions of characteristics? (Hermes & Poulsen, 2012a). If reweighting is selected, it is then necessary to choose between *deterministic* methods, which always produce the same result given the same inputs, and *probabilistic* methods, which sample from the microdata set and produce slightly different results each time the model is run[11] (Hermes & Poulsen, 2012a). If a deterministic algorithm is to be used, it may also be necessary to use an *optimisation* or *integerisation* on the model output, depending on the intended use of the outputs (Edwards & Clarke, 2013; Lovelace & Ballas, 2013). The interrelationships between these methods are outlined in Figure 2.

[11] Though it is possible to artificially limit the variability of stochastic processes by using the same random seed each time.

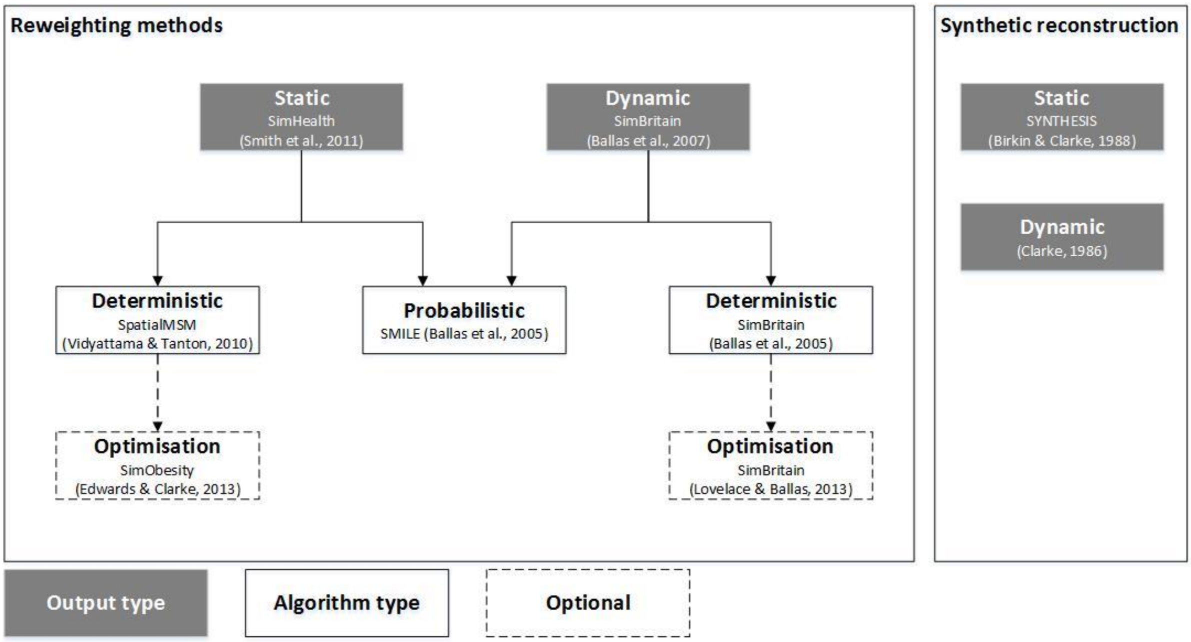


Figure 2.1: Relationships of different types of SMSM methodologies, with example references.

2.4.3 Policy analysis

SMSM is frequently promoted as being useful for policy analysis. Most often this is presented as a means of analysing 'what if' scenarios (Ballas et al., 2005a; Ballas & Clarke, 2001; Mitchell, Shaw, & Dorling, 2000). This description works well for analysing economic policy, for example: which areas would benefit if the government changed the eligibility for Working for Families[12] payments? How much would each family in that area gain on average? It is a simple task to identify the segment of the population that would be impacted by any proposed change, isolate these individuals within the synthetic population and estimate their prevalence in each area, and even to sum the expected total economic benefit to the area. Examples of this type of policy analysis are readily available from the UK (Ballas, Kingston, Stillwell, & Jin, 2007b; Ballas et al., 2005c) and Australia (Brown & Harding, 2002).

When it comes to formulating health policy, the situation is often less clear cut as public health policy seldom has a simple cause-and-effect outcome. Where SMSM can be of use in this respect is estimating the prevalence of a particular issue of concern in the population or

[12] Working for Families is system of government benefits, based on tax credits, for low to medium income families with children. The system has several different components, some of which require parents to be in work for a certain number of hours, others do not. For more information, see: http://www.workingforfamilies.govt.nz/.

sub-population. This type of estimate can be very difficult to obtain from traditional data sources. For some conditions, such as cancer or NIDDM, incidence in the population may be known very precisely due to statutory reporting requirements, or classification with International Statistical Classification of Diseases (ICD) codes and spatial data linkage. However, other conditions such as obesity do not have such classifications or requirements and are much more difficult to estimate with any degree of geographic detail. This is because of the limits of standard survey methodology, which tends to use a stratified, area based sampling methodology (for example: Ministry of Health, 2012b). This type of sampling means that the sample is drawn from only some of the small areas within the geographic strata (in Aotearoa New Zealand, DHBs); this enables a large area estimate at the stratified level, but not estimates for smaller areas.

Dynamic models, where life course events are modelled at each time stage for each individual, are particularly useful for health policy analysis. The incorporation of life course events (birth of a child, change in income etc.) allows the model to adjust the synthetic population, and potentially estimate the effects of different possible behavioural responses to a policy change (Ballas et al., 2006). However, this also introduces larger computational requirements, the potential for variation arising from stochastic methodologies, and higher risk of error if the event probabilities are incorrect.

SMSM enables the addition of health status to the selection criteria, beyond simple the demographic characteristics available from the Census. This is best illustrated with an example: such as reducing obesity in young adults. In order to do this, policy makers might try to identify areas with high numbers of young adults and target these. But not all areas with many young adults would exhibit high obesity rates in this population sub-group. This could be further refined to low SES areas with many young people, but the identified areas will still include areas with high tertiary student populations which are likely to be of less interest. In order to effectively target obesity in young people in small areas, it is necessary to have an estimate of the obesity rate in this target population for each small area, which is where SMSM comes in.

2.4.4 Health spatial microsimulation models

Obtaining accurate information about population health from any kind of survey — including the Census — can be problematic. Individuals are often reticent about providing personal details such as health information to a stranger. For example, there are some concerns about the smoking variable in the New Zealand Census, it was rated as being of moderate to high quality (fit for use) due to an elevated non-response rate (Statistics New Zealand, 2013c). Additionally there are known concerns with self-reported data, particularly for obesity (Ezzati et al., 2006). Accuracy issues and non-response can be reduced by using in-person survey methods, though these are expensive and the sample is necessarily limited (Ezzati et al., 2006; Ministry of Health, 2014c). Consequently, the ability of a SMSM to generate a synthetic population for a whole country or large region using high quality survey data collected through interviews is highly desirable and a wide variety of health research based on SMSM has been published.

SMSMs have been used to investigate a wide variety of different health topics. These include smoking in Leeds, and London in the UK, as well as Austria (Hermes & Poulsen, 2012b; Tomintz, Kosar, & Clarke, 2016; Tomintz, Clarke, & Rigby, 2008), access to and utilisation of GPs and other health services in rural Ireland (Morrissey, Ballas, Clarke, Hynes, & O'Donoghue, 2013; Morrissey, Clarke, Ballas, Hynes, & O'Donoghue, 2008), the spatial distribution of health inequities and their relationship to income (Ballas et al., 2006), several different aspects of ill-health (wellbeing, smoking, alcohol, and obesity) in Scotland (Campbell, 2011), retail food access and its relationship to diet-related disease in Leeds and Bradford in the UK (Smith, Clarke, Ransley, & Cade, 2006), psychological distress and alcohol consumption in England (Riva & Smith, 2012), the need for aged care services (Lymer, Brown, Harding, & Yap, 2009) and disability levels in older adults in New South Wales, Australia (Lymer, Brown, Yap, & Harding, 2008).

Many of these papers simply report on the construction of a model to address a particular problem and report on the findings of that model. However, a few provide health related results while reporting on a methodological problem. These include checking the accuracy of smoking estimates against Census smoking data in Aotearoa New Zealand (Smith et al., 2011), assessing the impact of input data set on smoking estimates (Hermes & Poulsen, 2012b), and a method for providing uncertainty intervals as well as point estimates for the health variable of interest — poor health in Wales in this case — a feature currently missing from most SMSMs (Whitworth, Carter, Ballas, & Moon, 2017).

A variety of different methods are used in Health SMSMs, though most methodologies selected are deterministic in nature. The most common methodology was *iterative proportional fitting* (IPF). This was used — with modifications in some cases — by researchers based or trained at the University of Leeds (Smith, Clarke, & Harland, 2007; Smith et al., 2006; Smith et al., 2011; Tomintz et al., 2008), and by those researchers' subsequent students (Campbell & Ballas, 2016; Riva & Smith, 2012). The next most common methodology used was *combinatorial optimisation* (CO), used by researchers from a variety of institutions. This was used in both deterministic (Tomintz et al., 2016) and probabilistic form — which includes a simulated annealing algorithm for optimisation (Hermes & Poulsen, 2012b; Morrissey et al., 2008). The final methodology is a generalised regression weighting procedure called *GREGWT* (Lymer et al., 2009; Lymer et al., 2008), which was developed at NATSEM, in Canberra, Australia.

Several models also carried out post-simulation analyses, beyond analysing the spatial distribution of their estimates. These analyses included using a spatial interaction model to relate the SMSM results to actual GP and hospital locations and assess accessibility of services (Morrissey et al., 2013; Morrissey et al., 2008), or to examine food outlet access (Smith et al., 2006), investigating optimal locations for stop smoking services using location-allocation models (Tomintz et al., 2008), and investigating change in smoking rates over time (Tomintz et al., 2016). These examples demonstrate the flexibility of SMSM outputs.

2.4.5 Spatial microsimulation models focusing on Obesity

SimObesity is a SMSM developed by Kim Edwards[13] to assess childhood obesity and obesogenic environments in Leeds (Edwards & Clarke, 2009; Edwards et al., 2009; Procter, Clarke, Ransley, & Cade, 2008). It was later expanded to include adult obesity in Yorkshire (Edwards & Clarke, 2013; Edwards et al., 2011). SimObesity demonstrates how SMSMs can be used to assess policy options, and recommended that different interventions may be more appropriate or more effective in different areas (Edwards et al., 2009; Procter et al., 2008).

In terms of model construction, SimObesity uses a deterministic CO algorithm with two microdata sets (Edwards & Clarke, 2013; Procter et al., 2008). Variables used to build the model included sex, age, an index of deprivation, qualification, ethnicity, tenure, household type, car availability, household size, and property type depending on the data set being used in the simulation (Edwards & Clarke, 2009; Procter et al., 2008). Validation methods were discussed at length in several publications (Edwards & Clarke, 2009, 2013; Edwards et al.,

[13] Née Procter.

2011), and additionally in a more recent publication discussing a new validation method using SimObesity as an example (Timmins & Edwards, 2016). Validation methods used included: linear regression models of constraint variables (used to build the model) comparing Census and simulated data sets (Edwards & Clarke, 2013; Edwards et al., 2011), a comparison between the simulated data and estimates generated from a national Health Survey (Edwards & Clarke, 2013), aggregating estimates to a larger geography and comparing to Census data (Edwards & Clarke, 2009), equal variance *t*-test (Edwards & Clarke, 2009; Edwards et al., 2011), comparing simulated data to small area data for cancer types known to be associated with obesity (Edwards et al., 2011).

SimObesity had two different key outputs: estimates of obesity itself, and estimates of obesogenic environmental variables. Methods of presenting information about obesity included maps (Edwards & Clarke, 2013; Edwards et al., 2011; Procter et al., 2008), cluster models (Edwards & Clarke, 2013), relative risk (Edwards & Clarke, 2013; Edwards et al., 2011), and hot and cold spots (Edwards et al., 2011). Several of the papers published also consider obesity at different scales (Edwards & Clarke, 2009; Procter et al., 2008). Information about obesogenic environmental variables was presented in both map and table form (Edwards & Clarke, 2009; Edwards et al., 2009; Procter et al., 2008). In (Edwards et al., 2009) obesogenic environmental variables were also compared to obesity estimates using geographically weighted regression (GWR).

Two other SMSMs have also focussed on obesity. The first examined obesity and dietary behaviours in Rio de Janeiro city, Brazil (Cataife, 2014). This model used CO and validated the results using total absolute error (TAE) and comparison to and official statistical estimates. The second examined obesity and spatial clustering in comparison to deprivation and food deserts in Detroit, Michigan, USA (Koh et al., 2015). These two papers specifically mentioned that SMSM was a useful or effective method for investigating small area obesity in their study area (Cataife, 2014; Koh et al., 2015). Papers about the SimHealth model do discuss obesity as an output in the context of constructing the model, but no estimates are presented (Smith et al., 2007; Smith, Clarke, & Harland, 2009).

2.4.6 Why use spatial microsimulation modelling over Census or NZDep?

Obesity is known to be strongly correlated with deprivation (Ministry of Health, 2016a), and this is expected to be reflected in the results from this thesis. It is worth asking the question, then, why is a SMSM necessary? Why not simply use deprivation, or even the Census smoking variable as a proxy? Both of these measures are already available from existing data, and do not require extensive additional work or testing. Alternatively, why not use another method for small area estimation?

Deprivation is not the only variable which affects the obesity rate, so it is possible for an area to be highly deprived and still return a relatively low obesity rate. For example, areas around Universities often contain high student populations,[14] students generally have very low incomes i.e. are likely to increase the deprivation of an area, but are also usually young i.e. have low obesity rates. How should an area like this be assessed in terms of obesity from a deprivation score or smoking rate? It will not respond in the same way as other areas, yet a SMSM is likely to be able to differentiate between this kind of area and other highly deprived areas based on the population composition in a way that the deprivation index cannot.

Census smoking data may be correlated with obesity due to its association with low SES. However, though individual smoking is correlated with body weight, the relationship is not simple. Smokers generally exhibit lower body weight than non-smokers, whereas individuals gain weight on quitting smoking (Klesges, Meyers, Klesges, & LaVasque, 1989). So as with the deprivation index, the Census smoking variable is unreliable as a proxy for obesity due to non-stationary interactions with other factors. Even if both deprivation and Census smoking data were good proxies for obesity, neither is able to provide an estimate of the obesity rate in a given area.

SMSM is not the only method available to generate small area estimates. A number of different methods which have been used to investigate obesity were discussed earlier (Sub-section 2.4.1). Other methods of small area estimation have been reviewed by Pfeffermann (2002) and employ complex statistical methods depending on the context of the analysis, examples included both frequentist and Bayesian approaches, Monte Carlo methods, time series, and multi-level models.

The key benefit to using SMSM in comparison to other small area estimation methods is that a full synthetic population for each small area is created, not merely a single point estimate for the area (Tanton, 2014). This means that a SMSM has the ability to subset a particular population by any definition, including the health variable of interest and then to provide a

[14] Particularly around the University of Otago in Dunedin

specific estimate of that variable in that population subgroup for a particular small area — a cross-tabulation. An additional benefit of SMSM, when using one of the simpler reweighting methods like IPF, is the relative ease of understanding — in comparison to a complex statistical analysis — when explaining the methodology to the intended audience: policy makers.

2.5 Summary: Obesity and geography

This chapter has demonstrated that obesity is the result of a complex interaction of personal and environmental factors, one with deep historical roots in the societal and food system changes of the preceding two centuries. The way in which obesity is measured and conceptualised and the contextual contributors to it has a profound impact on how both the public and health professionals view the 'obesity epidemic', how its 'victims' are treated, and the methods employed to mitigate or eliminate it.

SMSM offers a powerful tool for policy makers in its flexibility and ability to target specific sub populations or geographic areas. SMSMs are built using high quality, interviewer collected survey data but provide a synthetic population able to supply estimates at small Census geographies. Because SMSMs are built using individual level data, they are able to provide more information than an indicator variable such as deprivation, or a single health indicator like the Census cigarette smoking behaviour variable.

The purpose of this chapter was to address Objective 1: to review the literature around obesity and obesogenic environments, and the use of spatial microsimulation for health purposes. In addressing Objective 1, this chapter has demonstrated that there is a gap in the literature and information available to policy makers with respect to the small area geography of obesity in Aotearoa New Zealand. This thesis contributes a fine scale picture of obesity for use policy making, including estimates for specific areas.

Chapter 3 The Aotearoa New Zealand Context

The previous chapter broadly outlined the background context of obesity and obesogenic environments. It also highlighted a gap in current knowledge about obesity: its spatial distribution. The purpose of this chapter is to set the scene for the wider thesis by giving a brief overview of Aotearoa New Zealand, its health system, and what is currently known about obesity within the country.

This chapter will cover five topics specific to the Aotearoa New Zealand context. These are: the geography of Aotearoa New Zealand including the three main centres that will be highlighted in the results (Section 3.1), the social context including a brief history of the country and it's bi-cultural context (Section 3.2), the Aotearoa New Zealand health system including the DHBs responsible for each region (Section 3.3), obesity in Aotearoa New Zealand (Section 3.4), and health and Census data in Aotearoa New Zealand (Section 3.5).

3.1 Geography of Aotearoa New Zealand

As outlined above, this chapter provides a background on Aotearoa New Zealand for those unfamiliar with it. The purpose of this section is to explain key aspects of the geography of Aotearoa New Zealand as it is pertinent to this thesis, along with key Census geographies.

Aotearoa New Zealand is a small island nation in the southern Pacific with a largely temperate maritime climate and similar landmass to the UK. Aotearoa New Zealand consists of two main islands: the North Island (in te reo Māori: *Te Ika-a-Māui*) and the South Island (*Te Waipounamu*), along with several smaller islands including Stewart Island (*Rakiura*) off the southern coast, the Chatham Islands to the east, and many smaller islands. Figure 3.1 shows the overall geography of the country in the top left corner (excluding the Chatham Islands). The purpose of this section is to site the three main centres that will be used throughout the thesis: Auckland, Wellington, and Christchurch. This includes key locations within those cities, as well as introducing the DHBs (health administrative areas), and Census Area Units (CAUs — a census output geography). These three main centres are illustrated in the other three sections of Figure 3.1.

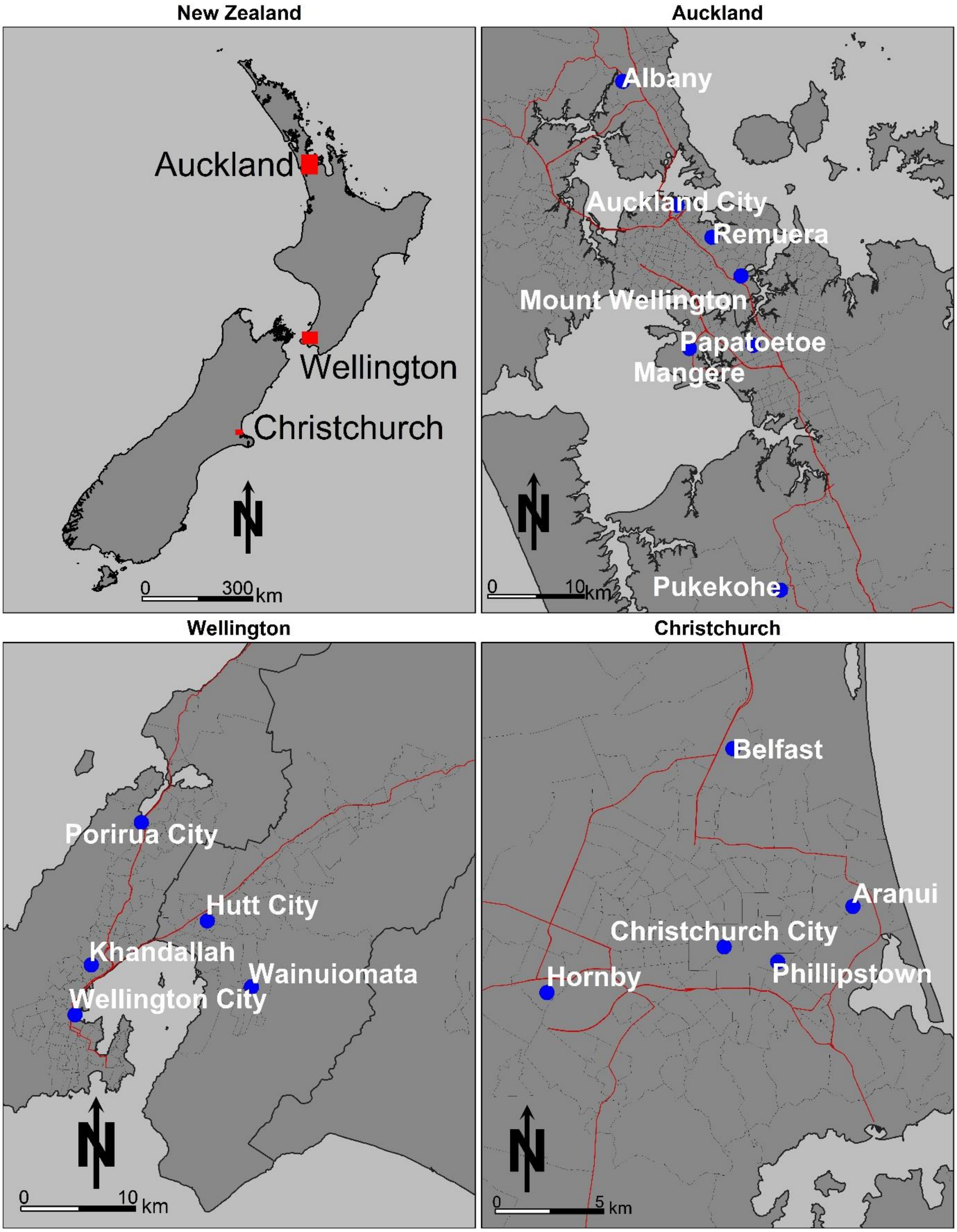


Figure 3.1: Locations of major cities, and key suburbs within cities. CAU boundaries shown in background, Chatham Islands not shown.

The three largest cities in Aotearoa New Zealand are Auckland, Wellington and Christchurch. Figure 3.1 shows the location of each city. The Chatham Islands are not shown in this, or any other figure in this thesis, as they are sufficiently far to the east to affect the size and proportions of the image. Most maps in this thesis will be presented for the whole of Aotearoa New Zealand with close views for each of the three main centres. Figure 3.1 also shows key locations within each city mapped in this thesis; these will be referred to in later chapters.

Census data are released at a number of different geographic scales. The smallest is the Meshblock (MB), varying in size from a city block to large tracts of rural land. MBs are contiguous across the whole country including the full extent of Aotearoa New Zealand's Exclusive Economic Zone, and they are the building block for every other areal unit used (Statistics New Zealand, 2006). For this thesis, the most important areal unit is the Census Area Unit (CAU), roughly the size of a neighbourhood. This is the scale at which the simulation estimates will be calculated and mapped, the reasoning for using this geography will be discussed in Sub-section 4.2.1. Also used are the Territorial Authorities (TAs) which are Aotearoa New Zealand's city and district councils, Regional Councils (RCs) which are responsible for environmental matters such as water and public transport — sometimes jointly with TAs, and DHBs — the health administrative areas (Figure 3.2). Mean population sizes at each of these geographic scales are shown in Table 3.1.

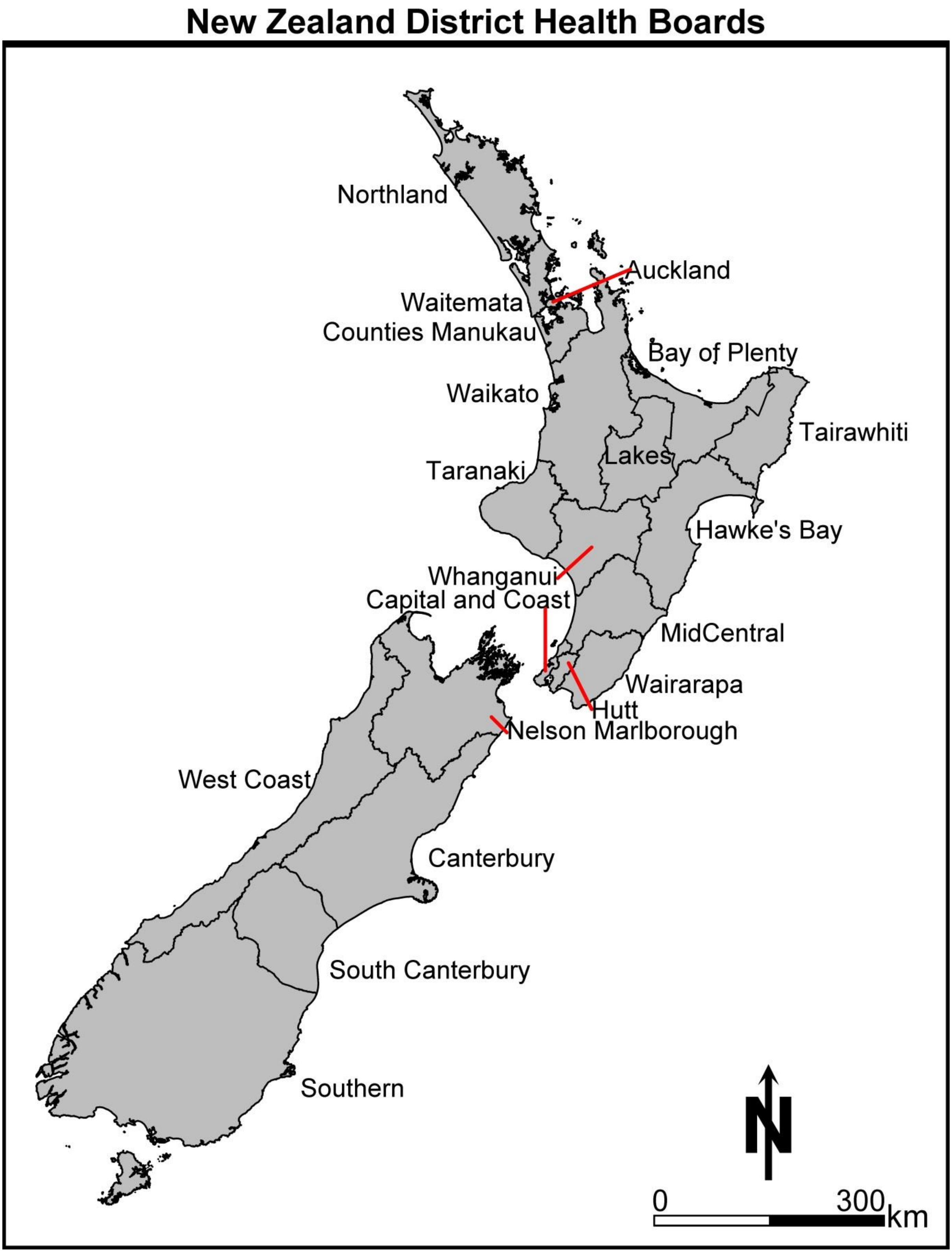


Figure 3.2: District Health Boards in Aotearoa New Zealand

Table 3.1: Census geographic areas used in this thesis.

Areal unit	Abbrev	N	Mean population	Min population	Max population
Meshblock	MB	46,621	91	0	1,899
(Census) Area Unit	CAU	2,012	2,108	0	11,700
Territorial Authority	TA	67	62,383	600	1,415,550
Regional Council	RC	16	265,090	32,148	1,415,550
District Health Board	DHB	20	306,934	26,001	417,570

3.2 Social context

The previous section described the geography of Aotearoa New Zealand and outlined some of the key areal units for Census data. This section will expand on that background to give a brief overview of the history of Aotearoa New Zealand, and the underlying social context.

Aotearoa New Zealand is a small nation, both by geography and population. The last Census showed a population of roughly 4.2 million (Statistics New Zealand, 2013e). Settled by Māori in the thirteenth century and later 'discovered' by European explorers in the seventeenth and eighteenth centuries, Aotearoa New Zealand formally became a British colony in 1840 with the signing of the Treaty of Waitangi. The scars of colonisation are still evident in poor health and social outcomes still experienced by many Māori today. Redressing these inequities is a key objective of Public Health policy and research in Aotearoa New Zealand, and some progress has been made (Boulton, Tamehana, & Brannelly, 2013).

The Treaty of Waitangi permitted the establishment of a civil government and brought Aotearoa New Zealand into the British empire (Waitangi Tribunal, 2017). The Treaty has two texts, an English version, and a *te reo Māori* version. Interpretation of the Treaty is difficult because the two versions have different meanings. Government agencies often rely on treaty principles, rather than the actual text of the treaty articles; though different agencies may use different sets of principles. The Waitangi Tribunal — a body that addresses breaches of the Treaty — does not use a single set of Treaty principles, because not all principles apply in all cases (Waitangi Tribunal, 2017). However, the Tribunal identifies a set of nine principles as an example on its website, these are: partnership, reciprocity, autonomy, active protection, options, mutual benefit, equity, equal treatment, and redress. The Ministry of Health (2014d) identifies key principles as: partnership, participation, and protection.

The majority of the population is of European descent, though there are large minorities of the indigenous Māori people, as well as Pacific and Asian ethnic groups — both South Asian (e.g. Indian), and East Asian (e.g. Chinese). The population in each of these groups is shown in Table 3.2, along with the composition of the three main centres that will be used later in the thesis. From this table, it is readily apparent that the ethnic composition of the country varies considerably among different locations. Not reflected within this table are the large Māori populations in Northland and Tairawhiti, Bay of Plenty, and throughout the central North Island. Maps showing the spatial distribution of each of these ethnic groups are available in 0.

Table 3.2: Ethnic composition of Aotearoa New Zealand[15] *and three major centres.*

	Total Aotearoa New Zealand	**Auckland Region**	**Wellington Region**	**Christchurch City**
European	74.0%	59.3%	77.0%	83.9%
Māori	14.9%	10.7%	13.0%	8.5%
Pacific Peoples	7.4%	14.6%	8.0%	3.1%
Asian	11.8%	23.1%	10.5%	9.4%

Note: based on New Zealand Census data (Statistics New Zealand, 2014a). Data are given for the Auckland Region (the entirety of the Auckland super city, covering three DHBs), the Wellington Region (three Territorial Authorities, or two DHBs), and Christchurch City[16], which is part of the larger Canterbury DHB, and has no other large urban areas nearby.

Aotearoa New Zealand has a large migrant population with approximately one quarter of residents born overseas. Historically most of this migration came from the UK and Ireland, but now the most common birthplace for migrants is Asia (Statistics New Zealand, 2014c). The most recent Census data also shows that Auckland is the region with the highest proportion of migrants.

[15] Note that the totals do not sum to 100% as individuals are able to select as many ethnic groups as they identify with.

[16] Note that the statistics for Christchurch city include the whole of the neighbouring Banks Peninsula, as this has been included as part of the city boundary since 2006. However, the maps do not include this area, as its geographic size dwarfs the city itself.

Aotearoa New Zealand is highly urbanised, with 86% of the population living in urban areas in 2006 (Statistics New Zealand, 2009b); estimates made using the updated 2018 Urban Rural definitions suggest that this has reduced slightly to around 84%[17]. One third of the population (33%) lives in Greater Auckland, 11% live in the Wellington region, and 8% live in Christchurch City (Statistics New Zealand, 2014a). Despite this, population density is low. This results in low density cities and a high reliance on car travel (Buchanan, Barnett, Kingham, & Johnston, 2006). This has consequences for health-related behaviours with more than 70% of the population driving themselves to work on Census day 2013 (Statistics New Zealand, 2015a). By extension rates of active travel are low: 7% walked and 3% cycled on Census day 2013 (Statistics New Zealand, 2015a).

There has been considerable concern about inequality in Aotearoa New Zealand in recent years. This has included both concerns over inequality itself (Rashbrooke, 2013), and concern about the housing crisis (Howden-Chapman, 2015). Social inequality in Aotearoa New Zealand is measured using NZDep, calculated using several Census variables at MB scale: internet access, means tested benefit, low equivalised income, unemployment, no qualification, renting, single parent households, access to a car, and household overcrowding (Atkinson et al., 2014). The spatial distribution of NZDep 2013 is shown at CAU level in Figure 3.3, a MB level map is available in Figure A.2. Māori and Pacific peoples are overrepresented among the most deprived (Theodore et al., 2015). More recent work offers a more complex and nuanced view than the single-measure NZDep (Exeter et al., 2017).

Aotearoa New Zealand had a GINI score — an international measure of inequality — of 33.1 in 2013, though this measure has shown some instability in recent years (Perry, 2017). Inequality (as measured by GINI) is much higher after housing costs, reflecting the greater proportion of income that is spent on housing costs in lower income households (Perry, 2017). In 2013, half of the population earned less than NZ$27,000, and 90% earned less than NZ$79,000 (based on data from Inland Revenue, 2016); the latter figure is comparable with the upper end of the pay scale for a Lecturer[18] at most Universities in Aotearoa New Zealand (Deloitte, 2012).

[17] Calculations made for this thesis based on (Stats NZ, 2018)
[18] Lecturer is the entry level for permanent academic positions in New Zealand, and is distinct from Senior Lecturer, Associate Professor, or Professor.

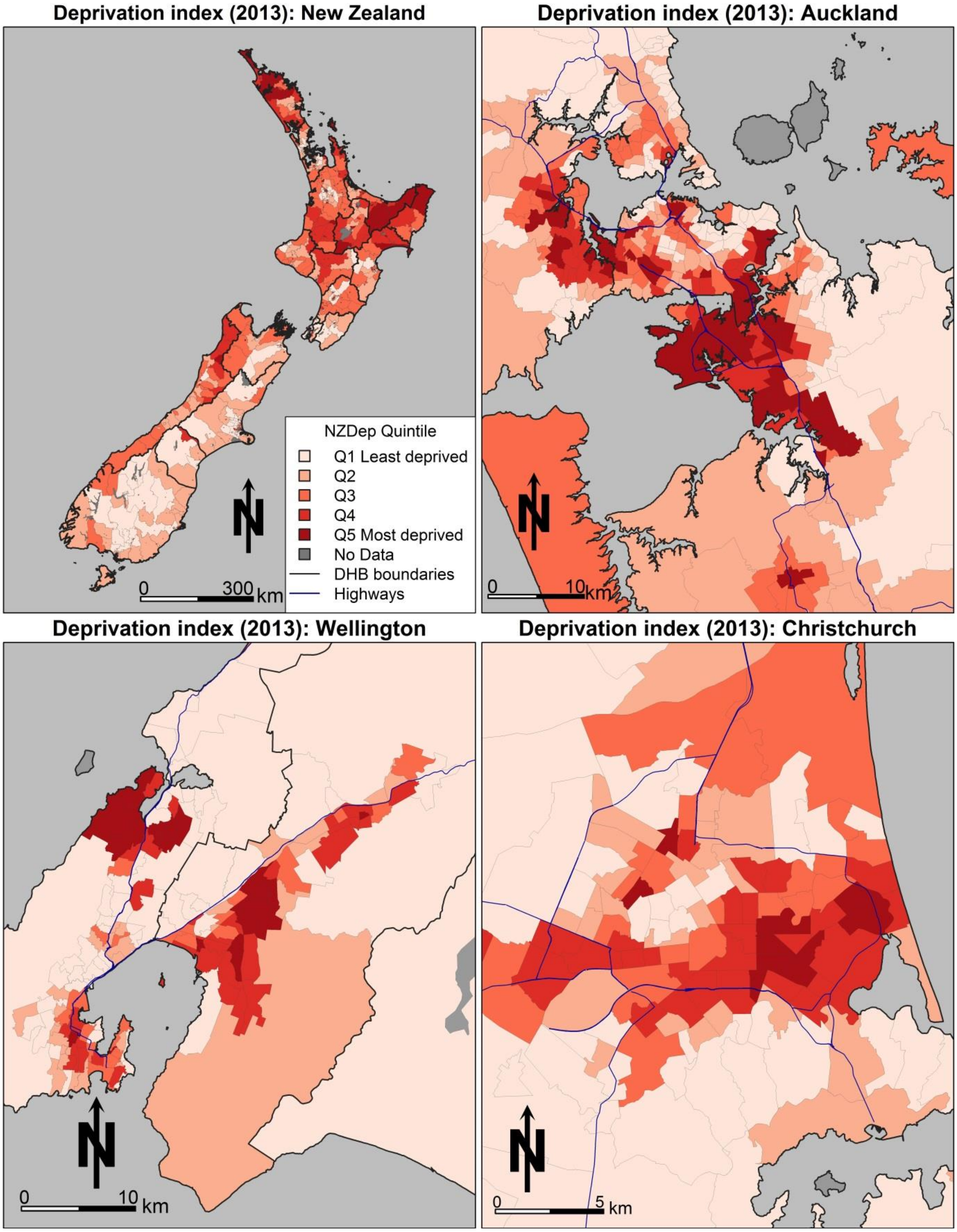


Figure 3.3: New Zealand Deprivation Index (2013) at CAU level, based on Atkinson et al. (2014).A MB level map is available in Figure A.2.

3.3 The health system in Aotearoa New Zealand

The previous section discussed the social context of Aotearoa New Zealand, including its colonial history, and economic inequities — two key determinants of health. This section will address the health system in Aotearoa New Zealand specifically, and additionally provide a brief background on Māori models of health.

Responsibility for most health services are divided up amongst 20 DHBs. This term refers both to the geographic areas as well as to the members of each board, elected alongside other local bodies every three years. DHBs are responsible for either providing or funding most health services within their region, though some services (e.g. disability support) are funded nationally through the Ministry of Health (Ministry of Health, 2017a). All accident related services are funded by ACC — the Accident Compensation Corporation (ACC, 2017; Ministry of Health, 2017d). Primary health care is funded by primary health organisations (PHOs) through DHBs. The DHBs have both a health service provision mandate and a social responsibility mandate. This can be seen in the list of DHB objectives outlined by the Ministry of Health (Ministry of Health, 2017a).

Regional public health services are delivered through public health units (PHUs). These are DHB owned, though several PHUs cover more than one DHB (Ministry of Health, 2017e). The PHUs include medical officers of health and health protection officers, they perform a variety of statutory functions relating to public health (e.g. tobacco control) and communicable disease monitoring (Ministry of Health, 2017e).

Health inequities experienced by Māori are a key matter of concern among public health professionals and academics in Aotearoa New Zealand. One method used to address this is the development of a specific Māori health strategy — *He Korowai Oranga* — embedded into all functions of the health sector (Ministry of Health, 2017b). A second strategy is to encourage and develop *kaupapa Māori* (using a Māori approach) service providers (Ministry of Health, 2014b). Māori models of health are more holistic than the standard biomedical model, explicitly including consideration of *whanau* (family), spiritual health, and other considerations depending on the specific model, alongside physical health (Durie, 2004; Ministry of Health, 2015b; Pere, 1991; Rochford, 2004). The absence of the spiritual dimension in many health services can be problematic for some Māori patients (Ministry of Health, 2015b).

3.4 Obesity in Aotearoa New Zealand

The previous section provided a general overview of the health system in Aotearoa New Zealand. This section will outline existing research on obesity in Aotearoa New Zealand. This includes existing Ministry of Health estimates of obesity rates in Aotearoa New Zealand.

The most recent estimate of obesity in Aotearoa New Zealand is 31.6%[19] from the 2015/16 wave of the NZHS (Ministry of Health, 2016a). The same survey report shows that obesity rates are higher among Māori (47.1%), Pacific Peoples (66.9%), and those living in the most deprived areas (44%). These results are reflected in the published literature (e.g. Utter et al., 2011; Utter et al., 2010).

As described earlier (Sub-section 2.1.4), Māori and Pacific Peoples register higher BMI values compared with a European person at the same percentage body fat. The ethnicity specific obesity rates reported by the Ministry of Health do not use ethnicity specific BMI cut-offs and thus overestimate obesity among Māori and Pacific Peoples by approximately 11 percentage points (Ministry of Health, 2008a). Similarly, the WHO BMI classification cut-offs underestimate obesity among Asian ethnic groups (WHO Expert Consultation, 2004), though this is generally of far less concern. Though there is an excellent rationale for using only the WHO BMI classification cut-offs (see Ministry of Health, 2008a), it does result in distortions for these ethnic groups.

Patterns of obesity in Aotearoa New Zealand are greatly influenced by the over representation of Māori and Pacific Peoples among those living in the most deprived areas. Since the 2006/7 NZHS, obesity among the least deprived areas has remained very similar (around 23%), whereas among the most deprived areas it has increased from 39% to 44% (Ministry of Health, 2016a). This indicates a growing health inequity among the most vulnerable populations. Using historical survey data, Ministry of Health (2004b) researchers demonstrated that the obesity epidemic in Aotearoa New Zealand likely began prior to the earliest available survey data (1977), but growth in obesity rates accelerated greatly during the late 1980s and early 1990s.

[19] The next wave of NZHS results are expected in late 2017, this may be after it is practical to make changes to this thesis but before examination.

Obesity rates are by no means equal throughout the country. The combined 2011-2014 NZHS data set gives an obesity estimate of 29.7%, slightly lower than the most recent single year estimate (Ministry of Health, 2015d). However, Auckland, Waitemata, and Capital and Coast DHBs exhibit significantly lower obesity rates than this, and Northland, Counties Manukau, Waikato, Lakes, Tairawhiti and Hawke’s Bay exhibit significantly higher obesity rates. By DHB, the lowest rate (21.8%) was observed in Auckland DHB, and the highest (37.7%) immediately to the south in Counties Manukau (see Figure 3.4). Changes in obesity rates between years are by no means static either; a comparison of DHB level obesity rates from the 2006/7 and 2011-14 survey analyses shows very little change in the obesity rate in Auckland, but rates increased substantially in Counties Manukau and Waikato (Ministry of Health, 2008b, 2015d).

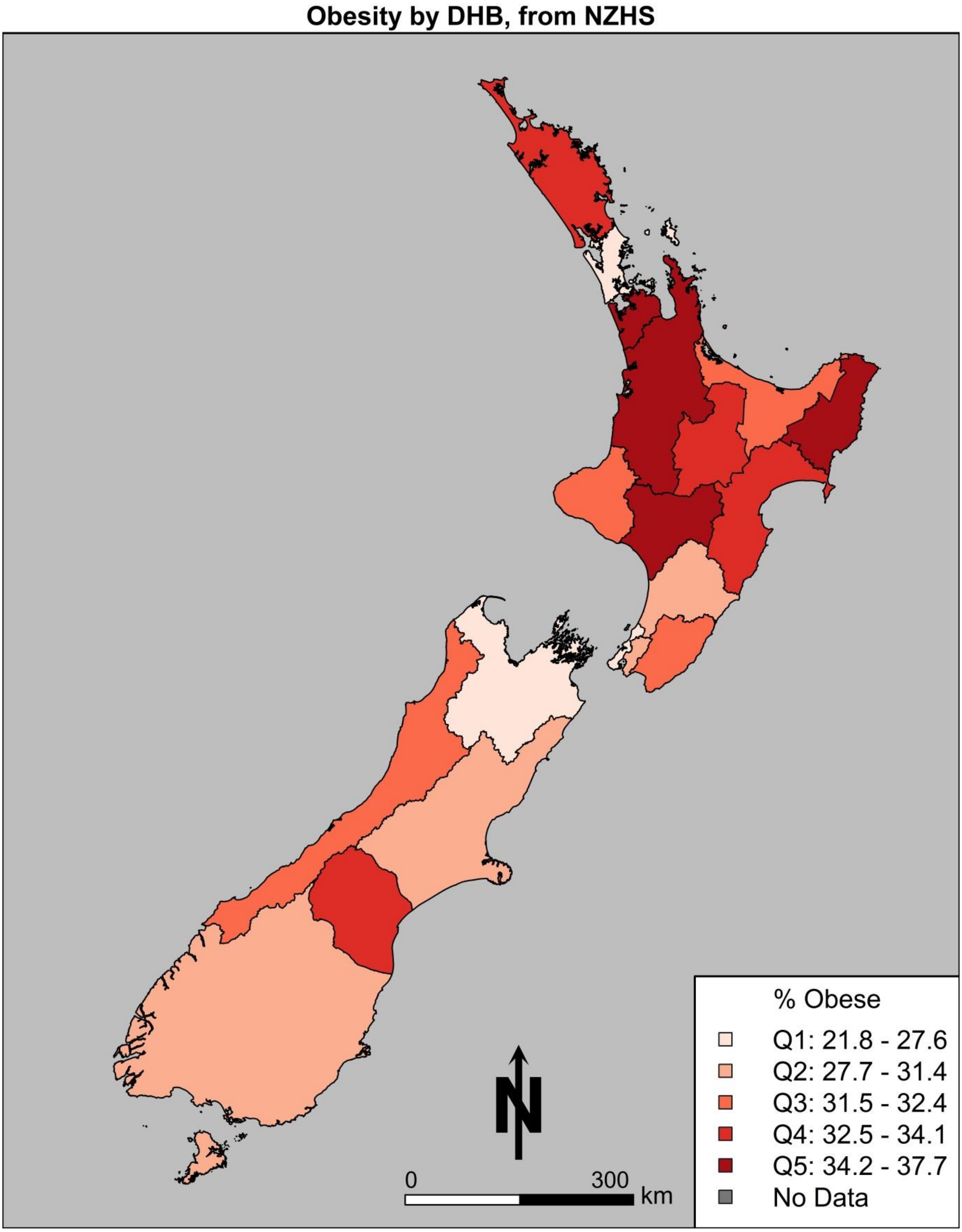


Figure 3.4: DHB level obesity rates, based on Ministry of Health (2015d).

Obesity in children is more common in urban areas (Hodgkin, Hamlin, Ross, & Peters, 2010), though there is no similar analysis for adults. In adults the highest rates are found between the ages of 35 and 74 (Ministry of Health, 2012a). Sex may also have an influence, at least for Pacific Peoples; one study showed that Pacific women were more likely to be overweight or obese than Pacific men (Sundborn et al., 2010). Not all of these findings are consistent, for example, Sundborn et al. (2010) found a lower risk of obesity in middle aged Pacific Islanders living in more deprived areas, however in contrast, Utter et al. (2010) found higher average BMIs in adolescent Pacific Islanders living in more deprived areas. While these are different age groups, greater similarity might reasonably be expected.

There are many published studies examining obesity in Aotearoa New Zealand. These can be split into three broad groups: firstly, those examining the prevalence of obesity in the population either nationally (e.g. Ministry of Health, 2012a; Wilson, Wilson, & Russell, 2001), within specific ethnic groups, usually Māori or Pacific Peoples (e.g. Gordon et al., 2003; Paterson, Taylor, Schluter, & Iusitini, 2013; Rush et al., 2007; Sundborn et al., 2010) or within particular age groups (e.g. Rush et al., 2013; Utter et al., 2010; Williams, Taylor, & Taylor, 2013). Secondly, those studies examining obesogenic environmental variables such as the positioning of food outlets (e.g. Day & Pearce, 2011; Pearce et al., 2007a; Vandevijvere et al., 2016) or walkability (e.g. Witten et al., 2012; Witten et al., 2011). And thirdly papers examining specific interventions or policy (e.g. Howden-Chapman & Chapman, 2012; Jenkin et al., 2011; Mandic, Bengoechea, Stevens, de la Barra, & Skidmore, 2012; Swinburn et al., 2011a; Walton, Signal, & Thomson, 2013). There are no currently published studies examining obesity at fine geographic scale, indicating a gap which can be filled by this thesis. The importance of understanding small-scale variations in the distribution of obesity was discussed in Sub-section 2.4.1.

3.5 Health and Census data in Aotearoa New Zealand

The previous section outlined the existing knowledge about obesity in Aotearoa New Zealand. The purpose of this section is to give an overview of the two main data sources used in this thesis, and to assess the available constraint variables. The first Sub-section (3.5.1) addresses the New Zealand Census, including confidentiality rules. The second Sub-section (3.5.2) describes the NZHS, including an outline of the methodology used.

3.5.1 Census

The New Zealand Census is (usually) taken every five years, with the most recent Census was conducted on 5 March 2013. Collection for this Census was originally intended for March 2011, but was delayed after the Canterbury earthquakes of September 2010 and February 2011 caused widespread population displacement (Campbell, 2015; Statistics New

Zealand, 2014b). Census data are publicly available from Statistics New Zealand and aggregated by geographical area, as discussed in Section 3.1.

Statistics New Zealand (2013a) has strict rules in order to prevent data from being released where individuals may potentially be identifiable. These include randomly rounding all outputs to base three, restrictions on the number of cross-tabulated variables available for small geographies, and the mean cell size of a table. These measures are important to bear in mind but should not have any significant impacts on the results.

The variables available from the 2013 Census are listed in Table 3.3. In order for the SMSM methodology to work, the constraint variables must be present in both data sets. Thus, it is important to assess which variables are available first. The 2013 Census questionnaire included a question about disability status, but these data are not reported by Stats NZ.

Table 3.3: Census variables 2013

Level	**Variables**
Individual	Usual resident population count, Census night population count, sex, age (5 year groups and broad groups), years at usual residence, usual residence 5 years ago (2008), birthplace, years since arrival in Aotearoa New Zealand (for overseas born), ethnic group, languages, Māori descent, religious affiliation, smoking, legally registered relationship status, partnership status in current relationship, tenure, fertility, qualification, study participation, personal income, sources of personal income, labour force status, employment status, occupation classification, industry classification, hours worked, travel to work (by home and work address), unpaid activities.
Family	Number of families in private dwellings, family type, family income, sources of family income.
Household	Number of households in private dwellings, household composition, number of usual residents, household income, sources of household income, tenure of household, sector of landlord, weekly rent, number of motor vehicles, access to telecommunications.
Dwelling	Private dwelling types, dwelling type (private/non-private), number of rooms, number of bedrooms, fuel types used for heat.

Note: from Statistics New Zealand (2014a)

3.5.2 New Zealand Health Survey data

The NZHS monitors the health of the population of Aotearoa New Zealand and provides evidence to support the development of health policy (Ministry of Health, 2013a). Previously, surveys were conducted irregularly and supplemented by other surveys on a specific subject (such as nutrition), however these have now all been collected together in a single health survey which operates continuously and reports results annually (Ministry of Health, 2013a).

The most recent NZHS (2015/16) contains the results of a sample of approximately 14,000 adults and 4,500 children throughout Aotearoa New Zealand (Ministry of Health, 2016a). The NZHS methodology report (Ministry of Health, 2012b) describes sampling methods and limitations. Briefly: the sample is drawn from a survey population of approximately 98% of the usually resident population of Aotearoa New Zealand. Those excluded from the survey are in places that are impractical to sample: certain types of non-private dwellings (such as prisons and hospitals) or households in very remote areas (such as on off-shore islands). The completeness of the survey coverage is important for accurate simulations (Hermes & Poulsen, 2012a). The methodology report also discusses the survey's multi-stage, stratified, probability proportional-to-size sampling method which draws both from MB (area based) samples and electoral roll samples. Ethnic minorities (Māori, Pacific and Asian) are deliberately over sampled in order to collect adequate samples of these important subgroups.

The NZHS methodology report (Ministry of Health, 2012b) also describes how data are collected. This is done by a trained interviewer through face-to-face, computer assisted interviews at a time convenient to the participant and their family. The methodology report also analyses response rate (the probability of a selected household actually participating) for the survey, this was 79% for adults and 85% for children. The overall coverage rate (which measures discrepancy between the sample and the population) for adults was 54%, with a rate of 68% for children. This included good coverage of Māori and Pacific ethnic groups, but poorer coverage rates in areas with higher social deprivation. The variation in coverage rates is handled by weighting the sample in the analysis of the survey (Ministry of Health, 2012b).

Variables available from the adult portion of the 2011/12 NZHS are described in Table 3 below. Three survey years were used in this thesis: 2011/12, 2012/13, and 2013/14. Data for children are collected, but this project used the adult data only. Confidentialised Unit Record Files (CURFs) from the NZHS contain no identifying information, including no spatial information, in order to preserve respondent confidentiality.

Table 3.4: Variables available from the 2011/12 NZHS for adults.

Subject area	Variables
Long-term health conditions	Heart disease, stroke, diabetes, asthma, arthritis, depression, bipolar disorder, anxiety disorder, chronic pain, oral health
Health service utilisation and patient experience	Usual primary care provider, GPs, primary health nurses, other nurses, after hours services, hospitals, emergency departments, medical specialists, oral health care workers, prescription medicines. Includes costs and barriers.
Health behaviours and risk factors	High blood pressure, cholesterol, physical activity, nutrition, tobacco use, alcohol use, drug use, gambling.
Health status	Health state, psychological distress.
Sociodemographics	Age, sex, ethnicity, birthplace, years since arrival in New Zealand, language, qualification, employment status, income (personal and household), tenure, number of bedrooms, sources of personal income, labour status, unpaid work, household composition, health insurance, racial discrimination, health insurance.
Area measures	NZDep, rurality based on the MB of the household.
Measurements	Height and weight, waist measurements.
Derived variables	BMI, NZiDep (individual deprivation), physical activity indicator.

Note: based on Ministry of Health (2012c).

Chapter 4 Design and validation of SimAotearoa

The preceding two chapters have provided the necessary background to understand the context in which SimAotearoa has been developed. Chapter 2 discussed existing research on obesity and obesogenic environments, as well as what can practically be achieved with standard statistical methods such as Bayesian smoothing, or regression of complex survey data. Chapter 3 discussed the Aotearoa New Zealand context, including what is currently known about obesity in Aotearoa New Zealand.

SMSM is a process that combines detailed but aspatial microdata with spatially specific Census data with a limited suite of variables. Variables common to both data sets, called constraints, are used to align the two data sets and weight microdata individuals according to how similar they are to residents of an area as determined by the New Zealand Census. The process thus produces a synthetic data set which is specific to each area, but contains the variables of interest from the more detailed microdata set. A basic outline of the steps involved in the SMSM process can be seen in Figure 4.1; appropriate validation of the model is critical to the success of the SMSM as this determines how well the model fits, and thus when the development process stops.

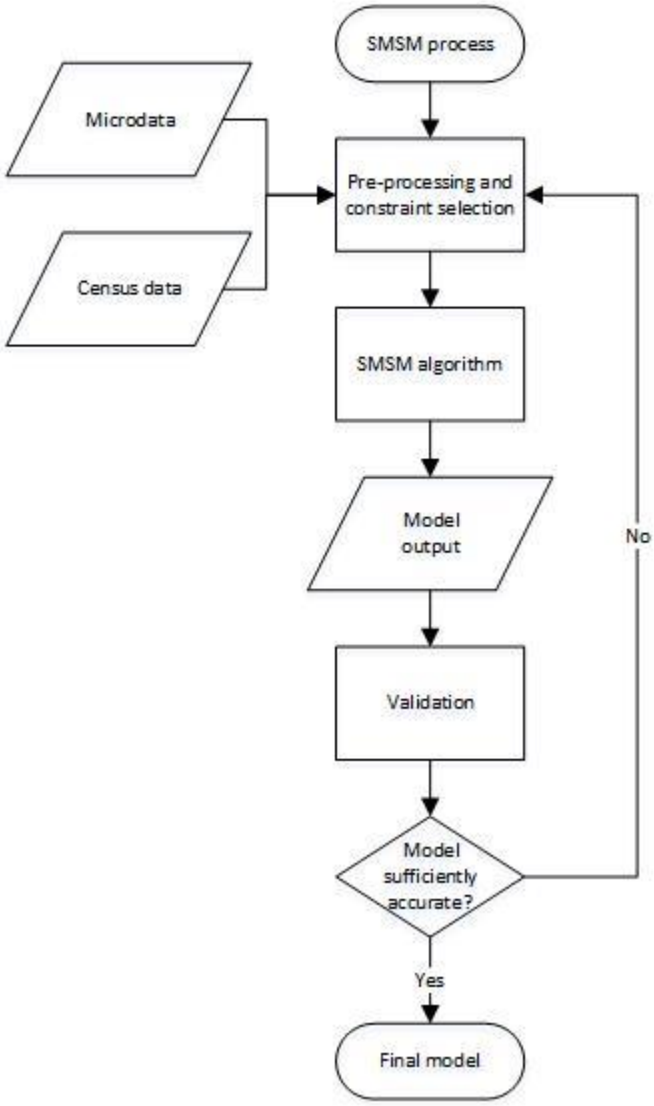


Figure 4.1: Outline of the SMSM process.

The focus of this Chapter is the construction and validation of the SimAotearoa model. The purpose of this chapter is to address Objective 2: to develop a spatial microsimulation model (SimAotearoa) suitable for estimating adult obesity and diabetes at a small area level in the Aotearoa New Zealand population in 2013; and to test the validity of this model. In order to achieve this objective, Section 4.1 first gives a basic background on the validation of SMSMs, as this is critical to the model building process. Then, Section 4.2 describes the methods used, including some particular issues around Aotearoa New Zealand ethnicity data. The model development and validation process is then illustrated in Section 4.3, and the results of the validation discussed in Section 4.4. Finally, the chapter will conclude by summarising the findings of the model construction and validation process in Section 4.5.

4.1 Introduction to model validation

The purpose of model validation is to determine to what extent the simulated model results are a reasonable representation of the real world. Indeed, this process is critical for researchers and end users to have any confidence in the accuracy of the model (Edwards & Tanton, 2013; Timmins & Edwards, 2016). To that end, the methods used to validate SMSMs are somewhat independent of the methodology used to generate the model because all methods involve the comparison of model outputs with another data set and assess the accuracy of these outputs. However, methodologies that derive confidence intervals are not suitable for use with deterministic methods as these rely on the variation produced by stochastic methods in order to calculate these intervals (Timmins & Edwards, 2016). This section will discuss the two key types of validation: internal (Sub-section 4.1.1) and external (Sub-section 4.1.2) validation, as well as a discussion of navigating conflicting perspectives on model validation in the literature (Sub-section 4.1.3).

4.1.1 Internal validation methods

The primary purpose of internal validation is to check that the model outputs match the data used to build the model and ensure that resulting simulated data set accurately represents the inputs. There is some disagreement as to how some of the validation methods should be classified. For example, at least one paper includes comparison of actual and simulated levels of the target variable at an aggregated scale as a form of internal validation (Timmins & Edwards, 2016), but others specify that a completely separate data set must be used (Edwards & Tanton, 2013).

There are a wide variety of validation methods in use, and several papers provide a review of the existing literature on validation methods (Lovelace, Birkin, Ballas, & van Leeuwen, 2015; Rahman, Harding, Tanton, & Liu, 2013; Timmins & Edwards, 2016). Common types of validation methodologies include correlation or R^2, TAE or standardised absolute error (SAE), standard error about identity (SEI), root mean squared error (RMSE), z-score and related measures, and E5. To briefly describe each of these (excluding standard statistical methods like R^2): TAE gives an absolute sum of the error — the difference between the simulated results and input (Census) data set regardless of whether the model results under- or over-estimates the validation data (Edwards & Tanton, 2013); SAE takes TAE and standardises it by the total population size (Edwards & Tanton, 2013); SEI measures the dispersion around a 45° observed = simulated line (identity) effectively removing the variation in population size (Tanton & Vidyattama, 2010); E5 is the count of absolute errors — where the simulated estimate varies by more than 5% from the value of the input data set (Lovelace et al., 2015).

Internal validation methods that have been used for previous obesity models include TAE (Cataife, 2014; Koh et al., 2015), comparison to aggregated data (Cataife, 2014), regression analysis (Edwards & Clarke, 2009; Edwards et al., 2011), equal variance *t*-tests (Edwards & Clarke, 2009; Edwards et al., 2011). New methods continue to be developed; for example Timmins and Edwards (2016) have proposed a new method of validation using Bland-Altman plots and demonstrated this using SimObesity.

4.1.2 External validation methods

The purpose of external validation is to check the accuracy of the model by examining how closely the model outputs correspond to data that was not used to constrain the model, thus how well it is likely to correspond to the unknown variable of interest (Edwards & Tanton, 2013). This type of validation is more rigorous than internal validation, and more context dependent. However, external validation of SMSMs is inherently problematic as this methodology is only used when there are no data available for the variable of interest at the desired spatial scale. Thus, it can be difficult to determine what constitutes a successful validation, how much agreement between simulated and validation data sets constitutes 'enough'? No SMSM can ever be validated exactly.

Some authors define external validation as occurring only where the comparison data set is completely external to the constructed model, not merely an unconstrained variable (e.g. Edwards & Tanton, 2013). Whereas, other authors use a broader definition that specifies only *"data not used in the simulation"* (Timmins & Edwards, 2016, p. 108). External validation of other obesity SMSMs has been relatively limited, however Edwards et al. (2011) used cancer rates for tumours associated with obesity. Aotearoa New Zealand smoking data has also been used to assess whether SMSM methodology was capable of producing accurate estimates of smoking rates as an indicator of whether this methodology is appropriate for use in countries where smoking data is not available from the Census (Smith et al., 2011).

Defining external validation as occurring only with a completely separate external data set in practicality sets the bar for true external validation extremely high. As external validation is the highest standard for validating SMSMs, this may well be reasonable. However, there is an argument for recognising methods that are an improvement over simply comparing the output data to the constraint variables used, but that do not meet this high standard for external validation. These intermediate methods are more rigorous than internal validation only (Smith et al., 2011), but are less rigorous than a fully independent external validation (Edwards & Tanton, 2013).

Data sets that were available for external validation of this model were the smoking data from the New Zealand Census, DHB and national level obesity estimates based on the NZHS, and the virtual diabetes register (VDR) — an interpolated data set generated by the Ministry of Health based on transactional data. Even these data sets present potential difficulties, for example, rates of undiagnosed diabetes are thought to be fairly high (Coppell et al., 2013). The possibility of using cancer data to provide a fully external data set for validation was raised with Ministry contacts, but proved impractical.

4.1.3 Validation perspectives

Different publications offer various, sometimes contradictory, validation strategies. Edwards et al. (2011) lists aggregating the output measure to a coarser geographic scale as an external validation method, but Timmins and Edwards (2016) list this as an internal validation method. Smith et al. (2011) do not specify whether they consider validation using an unconstrained Census variable (smoking) to be internal or external validation, however they make it clear that this is superior to using a variable unconnected to health (marital status) as a validation variable.

Consequently, it has been necessary to navigate among several conflicting perspectives and select strategies that are appropriate for an Aotearoa New Zealand context. For the purpose of the work presented here, internal validation will be used to indicate measures that compare the input data with the model outputs, i.e. testing the adequacy of the replication of the input data. In this thesis, external validation will refer to any method that assesses the accuracy of the model with respect to data not used as a constraint, i.e. testing the adequacy of the model against independent variables, including both smoking data and DHB level obesity estimates. This definition of external validation conflicts with some of the existing literature (e.g. Edwards & Tanton, 2013). However, differentiating this type of validation — against an unconstrained variable — from internal validation is important. External validation as defined by Edwards and Tanton (2013) — that it occurs only when using data from a different source — was not used here.

It should also be noted that validation standards and expectations continue to be updated. Since the work presented in this chapter was completed, new and improved methods of validation have been published (Timmins & Edwards, 2016), and undoubtedly more will follow.

4.2 Data and methods

The previous section discussed various validation methods and some of the considerations for using them. This section will discuss the various types of data used in SimAotearoa as well as the methods used in the model building process — including the validation methods selected.

This section is structured into six Sub-sections describing various parts of the data and methods. The section begins by describing the two main data sets — Census and NZHS data (Sub-section 4.2.1). Next, two data types that posed particular challenges are discussed: deprivation data (Sub-section 4.2.2), and ethnicity data (Sub-section 4.2.3). The section then moves on to the preparatory analyses that were conducted (Sub-section 4.2.4), and the SMSM process itself (Sub-section 4.2.5). Finally, the section will conclude by discussing the validation methods used (Sub-section 4.2.6).

4.2.1 Census and health survey data

Two separate data sources were needed for this analysis. The first is a detailed microdata sample from the NZHS (Ministry of Health, 2015c) containing individual records with both the constraint variables and BMI information, the second data source is New Zealand Census data (Statistics New Zealand, 2013d) describing the population of each area. Both were combined into the SMSM model, but each was also used in a preparatory analysis (discussed in Sub-section 4.2.4).

The microdata used for this analysis were individual records from three NZHS collection years: 2011/12, 2012/13, 2013/14 (Ministry of Health, 2015c), this provides a large sample from which to build the simulated data set, a method that has been used in other studies (e.g. Moon et al., 2007; Smith et al., 2009; Tanton & Vidyattama, 2010). The NZHS is discussed in greater detail in Sub-section 3.5.2, additionally the details of survey methodology and sampling design are available in the NZHS Methodology report (Ministry of Health, 2012b). Initially, only the first two years of this NZHS sample were used (n=22461), but this was expanded to three years (n=34955) to allow for a larger microdata set in order to construct DHB specific models as will be discussed in Sub-section 4.3.4. All individuals who declined to provide measurement data are excluded from these samples. The microdata are summarised for selected levels of potential constraint variables alongside 2013 Census data in Table 4.1 below.

Table 4.1: Summary of NZHS and 2013 Census data

	2-year sample	3-year sample	Census adults aged over 15
Total NZHS sample (n)	25,605	38,914	3,376,419
Retained sample (n)	22,461	34,955	NA
Retention rate (%)	87.7	89.8	NA
Mean BMI	28.5	28.6	NA
Underweight (%)	1.3	1.4	NA
Average (%)	30.6	30.1	NA
Obese (%)	34.3	34.1	NA
Overweight (%)	33.8	34.4	NA
Diabetes (%)	7.0	6.9	NA
Regular smoker (%)	21.4	21.7	15.1
Ex smoker (%)	28.3	28.4	22.9
Never smoked (%)	50.2	49.9	62.0
Males (%)	43.0	43.6	48.0
Least deprived areas (%)	13.4	13.1	20.6
Most deprived areas (%)	27.5	27.0	18.7
European (%)	73.1	73.2	74.8
Māori (%)	19.8	20.3	12.4
Pacific (%)	6.4	6.3	6.0
Asian (%)	7.8	7.9	11.7
Age 15-19 (%)	5.4	5.3	8.8
Age 20-24 (%)	6.9	6.9	8.6
Age 25-29 (%)	6.9	7.1	7.6
Age 30-34 (%)	7.9	7.9	7.6
Age 35-39 (%)	8.6	8.5	7.9
Age 40-44 (%)	9.4	9.4	9.1
Age 45-49 (%)	8.7	8.5	8.9
Age 50-54 (%)	8.8	8.9	8.9

	2-year sample	3-year sample	Census adults aged over 15
Age 55-59 (%)	7.7	7.8	7.7
Age 60-64 (%)	7.9	7.8	6.9
Age 65-69 (%)	6.7	6.8	5.8
Age 70-74 (%)	5.2	5.4	4.4
Age 75-79 (%)	4.3	4.2	3.2
Age 80-84 (%)	3.1	3.0	2.4
Age 85+ (%)	2.4	2.4	2.2
Employed (%)	58.5	58.6	62.3
Unemployed (%)	5.4	5.6	4.8
Not in Labour Force (%)	36.1	35.3	32.9
No Qualification (%)	40.6	39.8	20.9
School qualification (%)	8.7	9.2	40.0
Trade/Vocational qualification (%)	27.8	27.9	19.0
University qualification (%)	17.0	17.2	20.0
Own home (%)	61.6	0.0	49.8
Personal income $5,000 or less (%)	8.2	8.1	14.6
Personal income $50,001 or more (%)	21.9	22.8	26.7
Household income under $10,000 (%)	1.2	1.2	2.1
Household income over $150,001 (%)	5.5	5.9	13.3
Born in New Zealand (%)	NA	NA	71.1
Income from wages or salary	NA	NA	57.7
Income from a government benefit (%)	NA	NA	17.6

Area Units (CAUs) are the second smallest level of New Zealand Census data (Statistics New Zealand, 2013d), with an average total population size of 2108, including children. CAUs were selected as the primary unit for this analysis as there was limited ability to distinguish between adults and children at the smaller Census geography unit, MBs (mean population 91), due to privacy considerations. A large proportion of the cells in MB tables are confidentialised than in CAU tables, resulted in inaccurate simulation results due to lack of data for some variables; despite the larger average size, some small population CAUs were still excluded due to confidentialised data. The average adult population in the included

CAUs was 1826 across 1849 areas (from 2012 for which Census data is reported). The confidentialisation process also meant that there were small discrepancies among the various constraint tables (the table taken from the Census data set for a given variable across all small areas), thus all constraint tables were standardised to a single set of population totals drawn from one constraint table (qualification[20]). This process is similar to one used by Edwards et al. (2011), though the methodology differs.

CAUs are larger than several other similar SMSMs. In the UK, lower layer super output areas (LSOAs) used by Edwards and Clarke (2009); Edwards et al. (2011) had an average population of approximately 1500, and the smaller output areas (OAs) used by Campbell (2011) had an average population of 119. Outside of the UK, the Census tracts used by Cataife (2014) had an average population of 618. However, Koh et al. (2015) used areas with a larger average population of 3319 individuals (calculated based on information provided in the paper).

Census data were obtained for CAUs from NZ.Stat[21] (Stats NZ, n.d.). The Census data tables contained totals of usually resident adults aged 15 and over for each of the constraint variables selected (see Sub-section 4.3.1). Careful selection of Census tables on NZ.Stat meant that data excluding individual aged under 15 years old were obtained (by using tables that included data only obtained from individuals aged 15 or over, such as employment status or smoking).

4.2.2 Deprivation data

The New Zealand Index of Deprivation (NZDep) is used in many health-related studies in Aotearoa New Zealand as a measure of SES. NZDep is calculated from Census data to produce a deprivation score, which are further divided into deciles and reported as an ordinal

[20] All of the population totals for the tested constraint variables were very similar, within the limits of the random rounding used by Stats NZ (counts within 6 of each other). Qualification was selected as early runs of the model used the Meshblock data set, which did not allow for the exclusion of children from the sex and age variables; whereas the qualification data did not include children as this question was not asked of under 15 year olds. Qualification continued to be used throughout the modelling process to ensure consistency between model runs.

[21] Data for occupied private dwellings were also obtained by customised request from Stats NZ. This data was needed for tables about household income, which was considered as a possible SES variable for the SMSM. This data was used in the initial pre-SMSM analysis (shown in Table 4.8), but was not utilised further as other variables provided better fit in the SMSM. This may be partially because the sampling frame (occupied private dwellings) excludes non-private dwellings such as boarding houses which may have a bias towards more deprived individuals with high risk of obesity.

variable for MB areas, with each MB having a single assigned category (Atkinson et al., 2014). The variables used to calculate the index are: internet access, means-tested benefits, low income, unemployment, no qualification, dwellings not owner occupied, single parent families, overcrowding, and car access (Atkinson et al., 2014). For CAUs the score results are averaged across the constituent MBs and, again, reported as a decile. Note that though NZDep is reported on a decile scale, it has been condensed into quintiles for use here (i.e. reduced from ten categories to five by combining the 1st and 2nd decile into quintile 1 etc.). Both deciles and quintiles for deprivation are commonly used in health research in Aotearoa New Zealand and preliminary testing indicated minimal differences in the performance of the two categorisations within the model, but the quintile version was slightly favoured.

The single number reported for NZDep presents two challenges from a SMSM perspective. First, CAUs are large enough that they may contain several different levels of deprivation, and this may not necessarily be reflected by the overall CAU deprivation score. Second, the single value for a whole CAU means that only individuals with a matching NZDep score can be fitted to that area. However, NZDep is primarily calculated for the smaller MB geography, not CAUs, which means that the differences in geographic scale can be utilised to create a variable with multiple levels that reflects the heterogeneity of MB level NZDep values within a CAU.

In order to produce the deprivation variable used, populations for each MB within a CAU were assigned to the appropriate deprivation category. For example, a CAU containing 10 MBs, each with a population of 50 might have an assigned NZDep quintile of 2, but might contain MBs with NZDep quintiles ranging from 1 to 4. Thus, the levels of the NZDep variable for each CAU will represent the sum of the constituent MB populations at each deprivation quintile. This is illustrated by example 1 in Table 4.2, the table also contains two other examples for illustrative purposes. The patterning of CAU and MB level deprivation can be found in Figure A.1 and Figure A.2. A small number of MBs with large populations (mean population = 235) did not have an assigned deprivation value. These MBs were allocated to the deprivation quintile of the CAU in which they were situated.

Table 4.2: Distribution of deprivation scores for MBs which make up 3 example CAUs.

		Deprivation quintile				
		1	**2**	**3**	**4**	**5**
Example 1	Number of MBs	1	5	3	1	0
	MB Population in quintile	50	250	150	50	0
Example 2	Number of MBs	0	0	1	3	6
	MB Population in quintile	0	0	50	150	300
Example 3	Number of MBs	8	2	0	0	0
	MB Population in quintile	400	100	0	0	0

Note: all CAUs in this example have a population of 500 made up of 10 MBs each with a population of 50.

This approach of creating a multi-category deprivation variable at CAU level is more appropriate than using the single value of NZDep for each CAU for several reasons. Firstly, using a single value to represent a CAU restricts the model to selecting only individuals with a matching NZDep value. Despite this, apportioning MB level NZDep to CAU geographies allowed the model to exclude individuals from the sample who are very unlike the residents of any given CAU, while representing the (possible) heterogeneity in deprivation within the area. This is functionally similar to Birkin and Clarke's (2012) use of geodemographics to restrict their microdata sample to areas with the same geodemographic classification. Another advantage of using this approach to the deprivation variable is that the resulting variable exhibited strong within-area homogeneity, which few of the other available variables did (this will be addressed in Sub-section 4.3.1). The main disadvantage of this approach is that deprivation is an area-based characteristic, and individuals within each MB may not be well represented by their MB's deprivation value.

4.2.3 The challenge of Total Response: Using ethnicity data in the Aotearoa New Zealand context

Up to this point, ethnicity has been referred to as a single variable, which is an oversimplification used for clarity. In practice, the New Zealand Census and most statistical surveys in Aotearoa New Zealand (including the NZHS) use what is referred to as *total* *response* ethnicity, which permits respondents to select more than one ethnicity with which they identify. Ministry of Health ethnicity coding protocols are based on and consistent with the Stats NZ standard (Ministry of Health, 2017c). This methodology causes complications for SMSM as each ethnicity is best handled as a separate variable. This section will refer only to the highest, most general level of classification (e.g. both Indian and Chinese ethnicities are considered Asian etc.). This high level of classification generally is most appropriate for SMSM due to its robustness when dealing with small populations, as it is less likely to be confidentialised.

Most of the SMSMs described in the literature handle ethnicity very simply using a single variable with a small number of categories. This is consistent with the way ethnicity data is collected in censuses internationally. The UK Census requires individuals to identify with one ethnic category, which may include mixed ethnicity; approximately 2.2% of the population is of mixed ethnicity (Office for National Statistics, 2012). The USA Census allows the respondent to identify multiple categories as Aotearoa New Zealand does, but the proportion of the population who does so is approximately 2.9% (United States Census Bureau, 2011). The Australian Census collects information about ancestry and birthplace, which is not easily comparable with data from Aotearoa New Zealand (Statistics New Zealand, 2001).

The New Zealand Census and most surveys, use total response ethnicity rather than respondents specifically selecting a ‘multiple ethnicity’ category. Consequently, ethnicity data in Aotearoa New Zealand is reported for six major ethnic groupings: European, Māori, Pacific Peoples, Asian, Middle Eastern/Latin American/African (abbreviated to MELAA), and Other — which includes ‘New Zealander’ (Statistics New Zealand, 2014c). The sum of responses in across all categories is greater than the total number of individuals from which data is collected in almost all cases. Accurately reflecting multiple ethnicities in Census data is particularly important in Aotearoa New Zealand because the proportion of the population in Aotearoa New Zealand reporting multiple ethnic groups in 2013 was 11.2% — substantially larger than comparable countries (Statistics New Zealand, 2014c)

One possible solution to multiple responses for ethnicity described above would be to obtain data for Aotearoa New Zealand in *prioritised* form, essentially recording only one ethnic group even when multiple responses were given. Māori ethnicity has the highest priority under this system, anyone who identified themselves as Māori was always classified as

Māori. The other groups used were, in descending order of priority: Pacific, Asian, Other, and European (Statistics New Zealand, 2004). For example, an individual who identifies as Māori and European would be classified as Māori (see Individual 1 in Table 4.3). Someone who identified as Pacific and Asian but *not* Māori would be classified as Pacific (individual 3 in Table 4.3), and similarly an individual who identified as Māori and Pacific would be classified as Māori (individual 2 in Table 4.3). This is a particular problem as individuals who identify as Māori and Pacific are relatively common in comparison to other combinations of minority ethnicities. This process thus artificially reduces the size of the Pacific population (Statistics New Zealand, 2004). Pacific individuals are of particular interest from an obesity perspective (see Sub-section 2.1.4). Only those who do not identify as Māori, Pacific, or Asian would be classified as European/Other (individual 5 in Table 4.3).

There are four problems with the prioritised ethnicity approach. First, it overrides the principle of self-identification. Second, it artificially reduces the size of lower priority ethnic groups (Pacific Peoples in particular). Third, it does not consider the proportion of ancestry (i.e. someone who is ¼ Māori and ¾ Pacific would be classified as Māori, regardless of this weighting or their personal opinion), partially because this information is not collected. Fourth and finally, it does not adequately reflect the ethnic diversity of the population (Statistics New Zealand, 2004).

Table 4.3: Example individual Census responses and ethnicity classification

	Individual's Census response				**Prioritised**
	European	**Māori**	**Pacific**	**Asian**	**classification**
Individual 1	1	1	0	0	Māori
Individual 2	0	1	1	0	Māori
Individual 3	0	0	1	1	Pacific
Individual 4	1	0	0	1	Asian
Individual 5	1	0	0	0	European
Total responses (n = 5)	3	2	2	2	–

Other than using the prioritised approach, another possible solution to multiple responses for ethnicity is to treat each ethnic group as a separate variable; referred to here as the *four-variable* approach. This involves subtracting the number of responses for each of the four main ethnic groups (European, Māori, Pacific and Asian) from the total stated population in order to create a binary variable, for example “European” and “Not European”. To use the responses in the Table 4.3 above as an example (totals in the final line of the table), European would be 3, Not European would be 5 – 3 = 2. This method more accurately reflects the ethnic diversity of Aotearoa New Zealand, and is the preferred approach of the Aotearoa New Zealand national statistics agency (Statistics New Zealand, 2004), thus has been used throughout this thesis.

The MELAA and Other categories are both very small at 1.2% and 1.7% of the total population respectively (Statistics New Zealand, 2014c). These groups represent 0.9% and 1.3% of the NZHS sample. Consequently, due to sample and population size as well as lack of a significant relationship with either obesity or diabetes (discussed in Sub-section 4.3.1) it was judged best to not include these groups separately. They are represented among those who are “Not” any of the four main ethnic groups.

The high rate of multiple ethnicity in Aotearoa New Zealand is of particular importance for a SMSM. It is essential to reflect this in order to build an accurate simulation. Total response ethnicity will give a more accurate picture of the ethnic make-up of Aotearoa New Zealand, but it also represents a problem as the raw Census table will almost always add to a larger number than the population of any given area (for example, the last line of the Table 4.3 above sums to 9 from 5 individuals). Thus, total response ethnicity data cannot be used in a SMSM straight from a Census table, each ethnic group must be turned into a binary variable. To illustrate this, the example Table 4.4 below becomes the subsequent Table 4.5 a-d.

Table 4.4: Example area Census data and total response ethnicity

	European	Māori	Pacific	Asian	Sum of total responses	Actual area population
Area 1	400	50	30	100	580	500
Area 2	100	300	200	50	650	500

Table 4.5: Example area Census data with binary ethnicity variables

a	European	Not European	Total population
Area 1	400	100	500
Area 2	100	400	500

b	Māori	Not Māori	Total population
Area 1	50	450	500
Area 2	300	200	500

c	Pacific	Not Pacific	Total population
Area 1	30	470	500
Area 2	200	300	500

d	Asian	Not Asian	Total population
Area 1	100	400	500
Area 2	50	450	500

The four-variable approach will generate a more accurate picture of the population than a prioritised approach would, but it risks over-constraining the model. Earlier SMSM research recommended maximising the information available from the constraints, i.e. using the largest possible number of categories for each variable (Birkin & Clarke, 1988; Norman, 1999), but more recent research warns against over-constraining the model (Birkin & Clarke, 2012; Harland, Heppenstall, Smith, & Birkin, 2012; Lovelace et al., 2015). An over-constrained model is one where the model begins to fit less well as additional constraints are added. This can be a problem where there are too many levels within a variable, or when there are too many variables. Sub-section 4.3.3 discusses how the model was tested for over-fitting and will indicate that there was no evidence that using four-variable ethnicity reduced the fit of the model; thus four-variable ethnicity has been retained in the final model.

4.2.4 Preparation for spatial microsimulation modelling

Several analyses were undertaken in preparation for the SMSM process. The first two, regression and the *D*-statistic (Burden & Steel, 2015) were used to identify the best possible constraint variables. The third and last analysis, *k*-means, was used to help tailor the SMSM to different areas (Smith et al., 2009). Finally, a series of different candidate models was also developed in order to test which of the possibilities performed best in the SMSM.

The regression analysis was conducted using the NZHS data to assess the association between various possible constraint variables and obesity. The survey microdata were analysed with Maximum Likelihood Regression in the statistical software *R* (R Core Development Team, 2014), using the *survey* package (Lumley, 2014) in order to select the variables most strongly associated with BMI. The *survey* package uses the complex survey weights from the NZHS to generate estimates and analysis results that represent the national population, not just the individuals surveyed.

The *D*-statistic is a measure of within-area homogeneity. It was developed by Burden and Steel (2015) in order to assess differentiation between areas by variable. SMSMs show more success if they include at least some variables that are relatively homogenous within areas, with greater differences between areas. This allows the model to differentiate between different types of individuals and areas. Burden and Steel's (2015) methodology was replicated in *R* and used to analyse the Census tables of possible constraint data.

The Census data were also analysed using *k*-means in *R* to produce four non-contiguous groups of areas containing similar populations (Smith et al., 2009). Different candidate models were then developed and tested with each group of areas to assess whether each may be more accurately represented by different candidate models. The purpose of this procedure was to improve the accuracy of the results.

The final preparation for the SMSM was the selection of a series of candidate models using different permutations of the constraint variables. Consideration was given to changing the order of the variables in some models, but preliminary testing indicated this had very little impact on the results. Each candidate model was used to generate a separate SMSM, results and fit of each candidate model were analysed separately for each *k*-means group. The model which best fit each *k*-means group was then combined to make the final cluster model. This is one option to improve the fit of the model as it allows different models to be fitted for different types of areas (Smith et al., 2009).

4.2.5 Spatial microsimulation procedure for SimAotearoa

Much has already been written on how to construct a SMSM and the different types of modelling methods available (Edwards et al., 2011; Hermes & Poulsen, 2012a; Tanton, 2014; Tanton & Edwards, 2013; Timmins & Edwards, 2016). As discussed in Sub-section 2.4.5, a number of different methods have been used to generate SMSM of obesity. Methods that have been used previously include are primarily CO (Cataife, 2014; Edwards & Clarke, 2009, 2013) and IPF (Campbell, 2011; Koh et al., 2015).

The model described in this thesis, SimAotearoa, used a procedure called IPF (Ballas et al., 2005a; Norman, 1999), previously described in Sub-section 2.4.4 and outlined in Figure 4.2. The microdata sample — the NZHS data — here is represented by *M*, and the Census data by *A*. There are three main advantages to using IPF. First, that it is *deterministic* rather than stochastic, that is the model produces the same outputs when given the same inputs (assuming consistent variable order, etc.), which is important for a policy audience. Second, that it has a lower computational requirement than some of the available alternatives (e.g. simulated annealing), Third, the procedure is relatively simple to program and doing so enhances the user's understanding of the methodology and makes it more understandable to policy makers. The main drawback of IPF is that it produces 'fractional' individuals, which can be problematic for some applications of the synthetic data set. As there was no intention to use agent based modelling with SimAotearoa, or any other application where fractional individuals would present a problem, IPF was considered an appropriate method. IPF was selected as the reweighting methodology for SimAotearoa due to the advantages outlined above.

The main modelling process is computationally very simple. In order to calculate the new weight (*N*), both the Census (*A*) and microdata (*M*) are aggregated into single variable summary tables, the totals for each category in each area are then applied separately to the model formula (based on Anderson, 2013; Ballas et al., 2005a; Hermes & Poulsen, 2012a):

$$N = W\frac{A}{M} \qquad \textit{Equation 4.1}$$

Where the *W* is the current weight for each individual in the microdata (initial value 1), and the values used for *A* and *M* are the cells from the Census and microdata summary tables for the current variable in the current area. The calculated new weights for each individual are then stored. When the summary table for the next variable is calculated, the sum of the weights for each category is used, not simply the number of individuals in the category. The new tables are then fed into the same formula as before in the same manner, and the process continues to iterate. It is important that there is agreement between complete iterations of the model — this is called 'convergence' (Hermes & Poulsen, 2012a; Smith et al., 2009). In order to ensure this, the entire modelling procedure was repeated 20 times for every model. Twenty iterations ensured that all models reached agreement without excessive run time over what was absolutely required for the model to converge. The entire model was constructed in *R* specifically for this project using customised code.

The base SimAotearoa code could be used by anyone with a good working knowledge of *R* and a basic understanding of how SMSM works. One model run took a few hours[22] of elapsed time with the full SimAotearoa dataset (1849 areas, 38,914 individuals), depending on the number of variable levels included in the model. Running the model occurs in three stages. First, the data for the model (both census and survey) must be cleaned and appropriately formatted for the model; once this process is completed, it can be saved to an RData file for ease of reuse. Second, the model is initialised by creating storage arrays and matching variables between the two data sets, and then run. The outputs can then be saved to a CSV file once modelling is complete; the final output is a matrix giving the weight for each individual in each small area. Third and finally, the output must be processed into a useable format by summing weights for the individuals in each category for each area; this step can take considerable additional time, depending on how many variable levels and areas are being processed.

[22] Computer specs: 3.3 GHz Intel Xeon processor, 16GB DDR3 RAM, running Windows 7; model was run from an SSD drive.

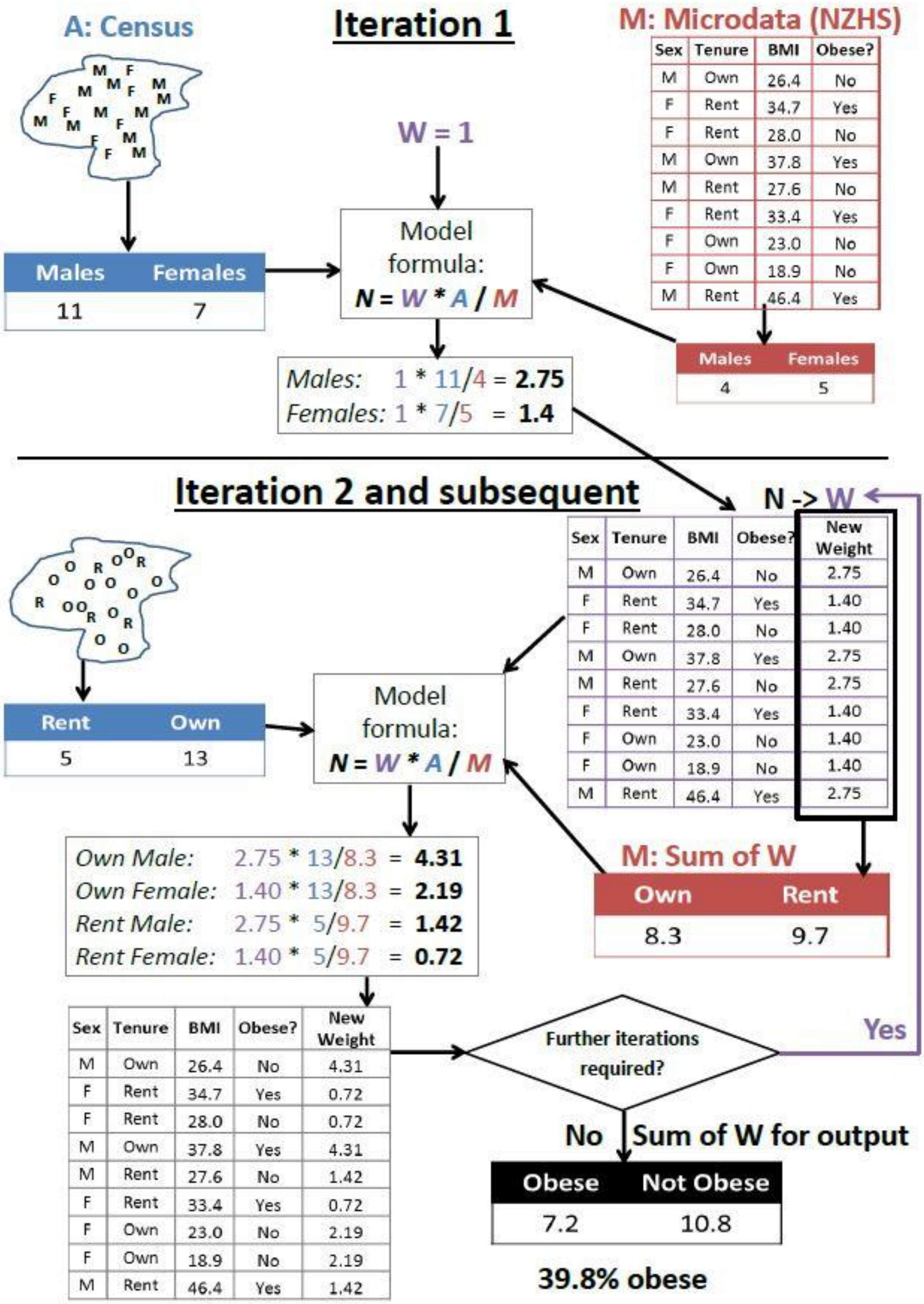


Figure 4.2: Stylised spatial microsimulation example

4.2.6 Validation methods and model outputs

Validation is a critical part of the modelling procedure. Section 4.1 discussed the wide variety of methods that have been used to validate other similar models. Only a small selection of these methods have been used here, these will be outlined below.

The internal validation processes concentrated on using TAE, both raw and as a proportion of the population for each small area (SAE). The formula for calculating TAE is as follows, based on Smith et al. (2009):

$$TAE = \sum_{ij} \left| S_{ij} - C_{ij} \right| \qquad \text{Equation 4.2}$$

Where *S* is the observed simulated count, and *C* is the expected Census count for the area *i* in category *j*. Although TAE is calculated by variable and area, it has been presented in the main text as totals across all variables and areas for the internal validation due to the very low error rates. In addition to this, SAE has been calculated in order to compare across areas as the absolute value of the error has a very different implication depending on the population size. SAE is calculated simply as TAE divided by the population of the area.

The external validation used unconstrained data from the data sets used to build the model. Data from a source external to the model was sought but not available. The New Zealand Census contains a smoking variable with three levels ('never smoked,' 'ex-smoker,' and 'current smoker'). These data were not used as constraints in the model and thus formed the main part of the external validation. TAE and SAE were also used here, but are presented separately for each level of the variable. Smoking TAE and SAE were assessed at CAU, national, cluster, and DHB level depending on the models being tested, though not all of these results are presented here. For the late stage models, the simulated and Census data for each level of the smoking variable are plotted directly against each other. Smoking SAE was also mapped by CAU for the final model.

Comparison of obesity rates aggregated to DHB scale were also used in the late stages of validation. For this, the simulated obesity estimates at DHB scale were compared to existing estimates calculated from the NZHS using standard statistical methodologies (Ministry of Health, 2015d). This form of validation was used to select among different possible models in order to identify the most appropriate model for each DHB.

Using data from the VDR as an external validation variable was considered. This register is a statistical estimate based on transactional data, not a traditionally sampled data set (Ministry of Health, 2017f). When tested as a possible validation variable at small area level, the register proved to have problematic spatial inconsistencies and incongruent estimates that prevented its use. Additionally, the version of the VDR that was available for validation was from 2011, this is an earlier and slightly less accurate version of the VDR than is now available; improvements made to the VDR are discussed by Jo and Drury (2015). This should not be interpreted as suggesting that the VDR is of low quality, merely that it is not intended for use at such a fine spatial scale.

4.3 Model building and validation results

The previous section discussed the data and methods used to build the SimAotearoa model. The purpose of this section is to present the results of the various analyses used to build and validate the model.

Five distinct stages were used in this process. First, possible constraints were identified and assessed for their relationship to obesity and diabetes as well as suitability for use in constructing the model (Sub-section 4.3.1). Second, several candidate models were identified using different possible constraint variables and microdata subsets (Sub-section 4.3.2). Additionally, CAUs were grouped into clusters of similar areas so that each could be fitted separately with a model that best represented that cluster's characteristics. Third, each candidate was tested for fit within each cluster and DHB, then grouped together to produce the final model (Sub-section 4.3.3). Fourth, models using different subsets of microdata in different DHBs were fitted and tested (Sub-section 4.3.4). Fifth and finally, the fit of the complete model was assessed and mapped (Sub-section 4.3.5).

4.3.1 Constraint selection

The first task in building the model was to assess the potential constraint variables. The variables available in the NZHS and Census were described in Section 3.5, an examination of these showed 11 possible constraint variables: age, sex, ethnicity, household income, personal income, birthplace, qualification, labour force status (LFS), housing tenure, sources of personal income, deprivation, and smoking status. Age and sex were considered important demographic variables to be included in the model in order to ensure that it is representative, thus no model without these was considered. These two variables were used as covariates in the initial regression modelling to select the possible constraint variables (see below).

Birthplace was considered as a variable but not used for several reasons. Perhaps most important of these is knowledge of the Aotearoa New Zealand context: the highest obesity rates are found among Māori (predominantly Aotearoa New Zealand born) and Pacific Peoples (mix of Aotearoa New Zealand and overseas born). The European population, much of which is also born in Aotearoa New Zealand, have much lower obesity rates, thus the usefulness of birthplace to identify obesity is likely to be limited. The *D*-statistic analysis (below) indicated that although birthplace was better than several other variables for distinguishing between areas, all of the ethnicity variables were superior. Additionally, in the early stages of the project, birthplace was tested in initial regression modelling with an older (2006) NZHS data set, although the results for obesity were significant, the effect size of the ethnicity variable was higher, particularly for Māori and Pacific groups. As birthplace was also absent from any previous literature around modelling obesity this variable was thus not requested from the new 2011-14 NZHS data set.

The categories used for qualification were slightly different between the NZHS and Census data. Consequently, these were condensed into four categories in order to align the two data sets: no qualification, school qualification, trade or vocational qualification, University degree or higher. The relationships between these categories can be seen in Table 4.6, teaching and nursing diplomas were classified as trade/vocational qualification as these represent sub-degree level qualifications. Additionally, there was a large non-response in both data sets which was included as a separate ‘refused to answer’ category.

Table 4.6: Concordance of SimAotearoa, Stats NZ, and NZHS data for highest qualification.

SimAotearoa variable	Stats NZ	NZHS
No qualification	No qualification	None
School qualification	Level 1 certificate	National Certificate level 1
School qualification	Level 2 certificate	National Certificate level 2
School qualification	Level 3 certificate	National Certificate level 3
School qualification	Overseas secondary school qualification	
Trade/vocational qualification	Level 4 certificate	National Certificate level 4
Trade/vocational qualification		Trade Certificate
Trade/vocational qualification	Level 5 or level 6 diploma	Diploma or Certificate level 5
Trade/vocational qualification		Advanced Trade Certificate
Trade/vocational qualification	Level 5 or level 6 diploma	Diploma or Certificate level 6
Trade/vocational qualification		Teachers Certificate / Diploma
Trade/vocational qualification		Nursing Diploma
University qualification	Bachelor degree and level 7 qualification	Bachelor
University qualification	Post-graduate and honours degrees	Bachelor Hons
University qualification	Post-graduate and honours degrees	Postgraduate Certificate / Diploma
University qualification	Master’s degree	Master’s Degree
University qualification	Doctorate degree	PhD

Logistic regression models were constructed for each of the remaining eight variables. These were adjusted for age and sex (Table 4.7) and used 2 years of NZHS data (2011/12 and 12/13). Although three years of data were used later in the modelling process when additional data was required to provide an adequate sample size, only two years of data were available for this initial set up. The four ethnicity variables and smoking were strongly related to obesity. Deprivation was clearly the best SES variable for predicting obesity, however, tenure, qualification and LFS also had good predictive power. Income (whether personal or household) was less strongly associated with obesity, with only a few income categories exhibiting significant relationships. Associations with diabetes were also strong for many of these variables, but both smoking and qualification were less strongly related to diabetes than they were to obesity. Both the MELAA and Other ethnicity groupings were tested, but not significant. The smoking column in Table 4.7 shows only current smoking compared with current non-smokers (never smoked and ex smokers elsewhere). However, this demonstrates that the constraints which will be later used to fit the SMSM model also predict smoking well, and justify the use of smoking as a validation variable for SimAotearoa.

One feature of SMSM is that in order for the model to distinguish among different types of populations, at least some of the constraint variables should have strong within-area homogeneity. One way of measuring this is the *D*-statistic (Burden & Steel, 2015), which is a measure of within-area homogeneity. A high *D* value indicates that areas tend to contain individuals of a similar type (i.e. high-income people live together, low income people live together and the two do not mix), rather than different types of people being mixed up among areas (i.e. many areas have a variety of different income levels). The results in Table 4.8 indicate that ethnicity (especially European and Pacific) and deprivation have reasonably strong within-area homogeneity but that other available variables do not. Also tested here is a ‘broad age’ group category where individuals were collected into broader age bands than the standard 5-year groups of the ‘age’ variable. This has not appeared previously as age was a covariate in the regression modelling. The categories for the broad age category are: 15-24, 25-44, 45-74, and 75+.

Table 4.7: Regression coefficients and standard errors (in brackets) for predicting obesity or diabetes with possible constraint variables.

Variable	**Level (reference)**	**Obesity**	**Diabetes**	**Smoking**
Personal income	$5,001 - $10,000			0.63(0.16)***
	$10,001 - $20,000	0.21(0.08)*		1.08(0.11)***
	$20,001 - $30,000			0.97(0.12)***
	$30,001 - $50,000		-0.41(0.18)*	0.74(0.11)***
	Over $50,001		-0.94(0.19)***	
	Refused to answer	0.21(0.09)*		1.05(0.10)***
	(Under $5,000)			
Household income	$10,001 - $20,000			0.73(0.19)***
	$20,001 - $30,000			0.42(0.17)*
	$60,001 - $70,000			-0.42(0.20)*
	$70,001 - $100,000			-0.58(0.19)**
	$100,001 - $150,000			-0.75(0.20)***
	Over $150,001	-0.44(0.20)*	-0.95(0.40)*	-0.94(0.22)***
	(Under $10,000)			
Deprivation	Second quintile			0.37(0.10)***
	Third quintile	0.33(0.07)***	0.55(0.17)**	0.57(0.09)***
	Fourth quintile	0.64(0.08)***	0.84(0.16)***	0.86(0.10)***
	Fifth quintile — most deprived	1.05(0.07)***	1.38(0.15)***	1.40(0.10)***
	(First quintile — least deprived)			
Housing Tenure	Rent (Own)	0.44(0.04)***	0.64(0.07)***	0.89(0.05)***
Smoking	Ex	0.35(0.04)***	0.24(0.08)**	N/A
	Regular	0.32(0.05)***	0.33(0.10)**	N/A
	(Never)			

Variable	Level (reference)	Obesity	Diabetes	Smoking
Ethnicity (Total Response)	European (Not European)	-0.54(0.05)***	-1.31(0.07)***	-0.35(0.05)***
	Māori (Not Māori)	0.94(0.05)***	0.83(0.09)***	1.24(0.05)***
	Pacific (Not Pacific)	1.84(0.09)***	1.56(0.14)***	0.37(0.09)***
	Asian (Not Asian)	-1.03(0.09)***	0.77(0.14)***	-1.04(0.09)***
Qualification	School			0.22(0.08)**
	Trade/Vocational	-0.21(0.05)***		-1.35(0.05)***
	University	-0.84(0.06)***	-0.46(0.13)***	-1.60(0.08)***
	Refused to answer (No Qualification)	-0.18(0.08)*		
Labour force status	Not in Labour Force	0.21(0.04)***	0.91(0.10)***	0.30(0.06)***
	Unemployed (Employed)	0.42(0.08)***	1.05(0.17)***	0.92(0.08)***

Note: *p < 0.05, **p < 0.01, ***p < 0.001. Uses 2011-13 NZHS data with age and sex included as covariates in all models. Only significant results are reported in this table.

Table 4.8: D-statistic values for variables.

Variable	D	k	Min (D_k)	Max (D_k)
Deprivation (quintiles)	0.303	5	0.181	0.483
Birthplace	0.119	2	0.119	0.119
Tenure	0.043	3	0.012	0.078
Qualification	0.03	5	0.007	0.072
Smoking	0.026	3	0.014	0.034
Household income[23]	0.018	10	0.003	0.081
Income Source	0.016	15	0.001	0.1
Personal Income	0.016	7	0.006	0.048
Labour force status	0.014	5	0.005	0.024
Sex	0.002	2	0.002	0.002
Age				
Broad age	0.032	4	0.023	0.038
Age (5-year groups)	0.015	15	0.01	0.037
Ethnicity				
Pacific	0.231	2	0.231	0.231
European	0.212	2	0.212	0.212
Asian	0.172	2	0.172	0.172
Māori	0.121	2	0.12	0.121

Note: a larger D indicates that the data set is more homogeneous by area, the k value indicates the number of categories. All data are from standard New Zealand Census data (Statistics New Zealand, 2013d) except where noted.

Based on these two analyses, the best variables available for SMSM were: ethnicity, age, sex, qualification, and deprivation, with smoking set aside as a validation variable. Tenure and LFS also performed well, and candidates with these variables will be considered. Personal and household income, along with birthplace and income sources have been excluded from use as they performed poorly relative to other possible constraints.

[23] Source: Statistics New Zealand, customised report and licensed by Statistics New Zealand for re-use under the Creative Commons Attribution 3.0 New Zealand licence.

4.3.2 K-means & candidate models

The *k*-means analysis is used with key Census data categories to group similar (but not necessarily contiguous) areas together. The concept behind the use of this for SMSM is that each cluster may be best represented by a different model, if each cluster is fitted separately the clusters can be combined into a final, better fitting model (Smith et al., 2009). The optimal number of clusters for this analysis was four, based on the sums of squares for different possible cluster sizes (see Figure C.1). Essentially, this is a balancing act between a manageable number of categories and extracting the maximum possible information from the data; the ‘ideal’ number of clusters is where the rate of change in the sums of squares reduces and the graph levels off. The final clusters are described below, with mathematical summaries in Table 4.9 and Table 4.10 (a more complete version of Table 4.9 is available in Table C.1).

Cluster 1: Slightly older population, with a largely even spread of age groups. Mostly European with some Māori. Relatively more deprived. Moderate levels of unemployment.

Cluster 2: Young population (many 20-34). Ethnically mixed, European majority with some Asian and Māori. Low rates of most deprived. Moderate unemployment rates.

Cluster 3: Older population. Almost entirely European with a small Māori population and others effectively absent. Least deprived. Low unemployment rates.

Cluster 4: Younger population (many 15-24). Ethnically diverse, all ethnicities. Highly deprived. High rates of unemployment, and high proportion not in labour force.

Table 4.9: Cluster characteristics, mean percentage in key categories.

Cluster	Male	45 years or older	Not European	Most deprived	Unemployed
1	47.65	52.39	24.06	40.69	6.02
2	48.98	41.04	38.72	6.84	5.04
3	49.17	57.17	10.66	2.35	3.10
4	48.14	46.16	56.24	85.14	9.60
All	48.80	52.72	22.05	17.94	4.56

Table 4.10: Distances between cluster centres.

	Cluster		
Cluster	**1**	**2**	**3**
2	38.63		
3	41.03	32.73	
4	55.34	80.53	95.37

Based on these clusters, several candidate models were developed for the different clusters. An age variable with fewer categories (four instead of fifteen) was also included to evaluate whether the large number of levels in the age variable might contribute to over-fitting in the model. In descending order of priority, the variables included were: SES (LFS, qualification, or tenure), ethnicity (Pacific, Māori, Asian, European), deprivation, age, sex. Not all variables were included in every model. The variable levels are described in Table 4.11 with the candidate models in Table 4.12.

Table 4.11: Constraint variable levels

Variable	**Categories**
Sex	Male, Female
Age	5-year groups: 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80-84, 85+
Broad age	Broad groups: 15-24, 25-44, 45-74, 75+
European	European, Not European
Māori	Māori, Not Māori
Pacific	Pacific, Not Pacific
Asian	Asian, Not Asian
Deprivation (NZDep)	Quintiles 1 (least deprived) to 5 (most deprived)
Highest qualification (Qual)	No qualification, School, Trade or vocational, University, Refused to answer
Tenure	Rent, Own
Labour force status (LFS)	Employed, Unemployed, Not in labour force (NILF)

Note: some variables have an abbreviation listed in brackets.

Table 4.12: Candidate models with variable ordering

Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**
Sex	Sex	Sex	Sex	Sex	Sex	Sex	Sex	Sex
Age	Broad age	Age	Age	Age	Age	Age	Age	Age
NZDep	NZDep	NZDep	NZDep	NZDep	NZDep	NZDep	NZDep	NZDep
European	European	European	European	European	European	European	European	European
Asian	Asian	LFS	Māori	Asian	Māori	Asian	Asian	Asian
Māori	Māori		LFS	LFS	Pacific	Māori	Māori	Māori
Pacific	Pacific				LFS	Pacific	Pacific	Pacific
Qual	LFS					LFS	Tenure	

The models in Table 4.12 were initially constructed using only one SES variable (i.e. models 1, 7, and 8 were originally built with qualification, LFS and tenure in place of deprivation rather than in addition to), but deprivation performed much better than the other SES variables considered. Consequently, this was kept as the 'base' model (model 9) and a second SES variable was added (models, 1, 7 and 8). The best of these models was then also modified to assess the possibility of over-fitting by swapping to use broad age categories and constructing models with different ethnicity profiles (and thus also a different number of variables, these are models 2-6). Models 3-6 also serve to test whether specific ethnicity profiles may better suit some of the clusters identified above. A reduced ethnicity category model was not tested in conjunction with broad age categories.

The possibility of changing the order of constraint variables was considered and tested. This can change the model results (Smith et al., 2009), though Lovelace et al. (2015) found that the most important consideration is the number of categories used in variables fitted later in the process. Models with deprivation fitted last performed poorly in preliminary testing due to the way the deprivation variable was built, thus the final variable in each model is either an alternative SES variable or an ethnicity variable, all of which contain a small number of categories — ethnicity and tenure variables are binary, labour force status has three categories, and qualifications has four. Preliminary testing showed that while the outputs of differently ordered models were not identical, the differences were incremental and not meaningful. As reordering the variables would substantially increase the number of candidate models, only one variable order is considered here.

4.3.3 Candidate model validation

Once the clusters and suitable candidate models were identified, these nine candidate models were constructed and tested. The *R* code used to construct the SMSM model can be found in Appendix B. The *R* code has been made available to facilitate the reproducibility of this research.

The first step in validating the model is to check that all constraint variables fit very closely to the constraint data. For this purpose, TAE was used as discussed in Sub-sections 4.1.1 and 4.2.6. Summary statistics for the TAE of the simulated population for each model across all constraint variables are presented in Table 4.13 below, summary statistics by variable are available in Table C.2, Table C.3, and Table C.4. The most important values in the table are the spread between the mean and the median, the actual values of the mean and median error and the TAE (Smith et al., 2009). Lower values indicate better performance. The lowest spread value came from model 1, though all models except model 2 were comparable on this variable. The lowest TAE was exhibited by model 9 and the highest by model 1, with the other models clustered in between these two extremes. This suggests that estimates in model 1 are closer together, but at the expense of higher overall error; this is unlikely to be a desirable quality in the final model. Table 4.13 also presents the percentage of CAUs with SAE >20% across all variables, this is an indicator of poor fit in SMSMs (Smith et al., 2011), and was very low in all models.

In order to generate the external validation results using the unconstrained Census smoking variable, the Census smoking data were scaled to the adult population of the area. The reason for this is that, nationally, approximately 5% of the population refused to answer the question on smoking in the Census, resulting in a small discrepancy between the raw number of responses recorded and the total adult population in the CAU. Only 109 individuals who did provide measurement data refused to answer the NZHS smoking question from total 25,605 NZHS respondents (in the two-year sample, 164 in the three-year sample), this is not enough to realistically model this ‘refused to answer’ group separately. Consequently, the simulated data will consistently slightly overestimate the number of people in each smoking category relative to the raw number stated in the Census. Scaling the count of the number of people stated to the total adult population is not an ideal use of Census data but does remove this discrepancy.

The external validation using the Census smoking variable is presented in the same manner as the internal validation above, using TAE and SAE, except the results are presented separately for the three levels of the smoking variable. The fit of model 3 was very poor across all smoking categories (Table 4.14), with high TAE, high spread and high mean and median errors. The fit of models 1, 2 and 8 were also poor, for similar reasons. Models 4, 5 and 6 were not obviously poor performers, but neither were the key measures for these particularly good. Model 7 and model 9 provided the best fit, particularly in the never smoked and regular smoker categories, where they had among the lowest results for each of the four key measures (TAE, standard error, spread, and mean and median values). As discussed in Sub-section 4.3.2, models 2 through 6 were included with fewer categories or constraints specifically to test whether the model was over-constrained. The poor performance of these models relative to both model 7 and model 9 indicates that the model is not over-fitted and that the four-variable approach to ethnicity is appropriate for use in SMSM.

Table 4.13: Summary of internal validation errors across all constraint variables in all models

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Median	0.14	0.00	0.15	0.13	0.13	0.11	0.09	0.08	0.09
Mean	0.41	0.64	0.44	0.43	0.43	0.41	0.40	0.39	0.37
Spread	0.27	0.64	0.29	0.30	0.30	0.30	0.31	0.31	0.28
Minimum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Maximum	22.19	22.19	22.19	22.19	22.19	22.19	22.19	22.19	22.19
TAE	23,655	21,377	21,236	21,236	21,244	21,236	21,375	20,319	17,739
% SAE > 20%	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Although the TAE values may appear high, these values represent between 2.9% (model 1 for ex smoker) and 8.6% (model 3 for never smoked) of the total adult population. These proportions are roughly consistent with (but not the same as) the mean SAE values given in the table. For example, Model 7's never smoked TAE is equivalent to 6.8% of the adult population compared with a mean error of 6.2%, and the regular smoker TAE for the same model is equivalent to 3.8% of the adult population compared with mean error of 3.6%. Error values for the never smoked group are larger because this group is a larger proportion of the population; consequently, an error of the same proportion will have a higher absolute value from the never smoked category than either of the other two.

Histograms of residual errors and scatter plots of Census and simulated population estimates are shown in Figure 4.3 for Candidate 7 and Figure 4.4 for Candidate 9. The performance of these two models was very similar, however Candidate 7 showed slightly fewer errors above the 20% threshold. Additionally, candidate 7 had slightly more clustering around the 1:1 line of best fit; this is most visible for regular smokers.

After the models were validated at small area level, the results were aggregated to a geographical scale (DHB level) for which existing estimates of obesity were available (Ministry of Health, 2015d). On examination of the results of this analysis (see Table 4.15), it rapidly became apparent that the cluster model approach did not offer any improvement over the single models for estimating obesity at DHB level. Thus, the cluster models were rejected as the additional complexity offered no accuracy benefits. The full cluster validation results are available in Table C.1. Without the use of the clustered model, there was no need to retain models 3-6 as they were developed for use in specific clusters and don't accurately represent all ethnicities.

Table 4.14: Summary of external validation errors for three smoking categories in all models.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**
Never Smoked									
Mean	7.06	6.49	7.07	6.20	6.53	6.21	6.19	7.43	6.29
Median	6.99	6.38	5.84	5.68	5.99	5.74	5.98	7.27	6.08
Spread	0.07	0.11	1.23	0.52	0.54	0.47	0.21	0.16	0.21
Std Error	3.23	3.16	5.19	3.64	3.72	3.47	3.12	3.64	3.13
Minimum	0.00	0.00	0.00	0.00	0.02	0.00	0.01	0.01	0.00
Maximum	40.96	40.69	40.29	39.79	40.35	39.59	39.62	45.51	39.56
TAE	257,441	238,199	290,394	237,607	252,011	236,250	228,817	274,863	231,025
% SAE >20%	0.59	0.38	3.14	0.43	1.46	0.43	0.32	0.70	0.43
Ex smoker									
Mean	3.08	3.75	3.74	3.52	3.59	3.50	3.50	3.49	3.52
Median	2.82	3.56	3.37	3.26	3.34	3.24	3.30	3.25	3.32
Spread	0.26	0.19	0.37	0.26	0.25	0.26	0.20	0.24	0.20
Std Error	1.38	1.56	2.04	1.66	1.64	1.65	1.49	1.49	1.49
Minimum	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01
Maximum	21.61	22.72	21.78	21.67	21.91	21.76	21.94	20.57	20.34
TAE	99,148	125,182	135,073	120,347	122,236	119,574	115,802	115,092	116,306
% SAE >20%	0.05	0.11	0.11	0.11	0.11	0.11	0.11	0.05	0.11

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**
Regular Smoker									
Mean	4.70	3.65	4.34	3.67	3.89	3.68	3.62	4.64	3.65
Median	4.74	3.37	3.53	3.28	3.40	3.36	3.31	4.38	3.37
Spread	0.04	0.28	0.81	0.39	0.49	0.32	0.31	0.26	0.28
Std Error	2.19	2.00	3.53	2.41	2.47	2.22	2.05	2.59	2.05
Minimum	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.01
Maximum	21.08	22.85	26.03	22.76	24.03	22.21	22.22	27.14	22.07
TAE	168,757	126,393	170,623	132,452	143,444	131,813	126,914	169,388	127,954
% SAE >20%	0.22	0.16	0.38	0.16	0.11	0.16	0.11	0.22	0.22

Note: Numbers refer to SAE values unless otherwise specified.

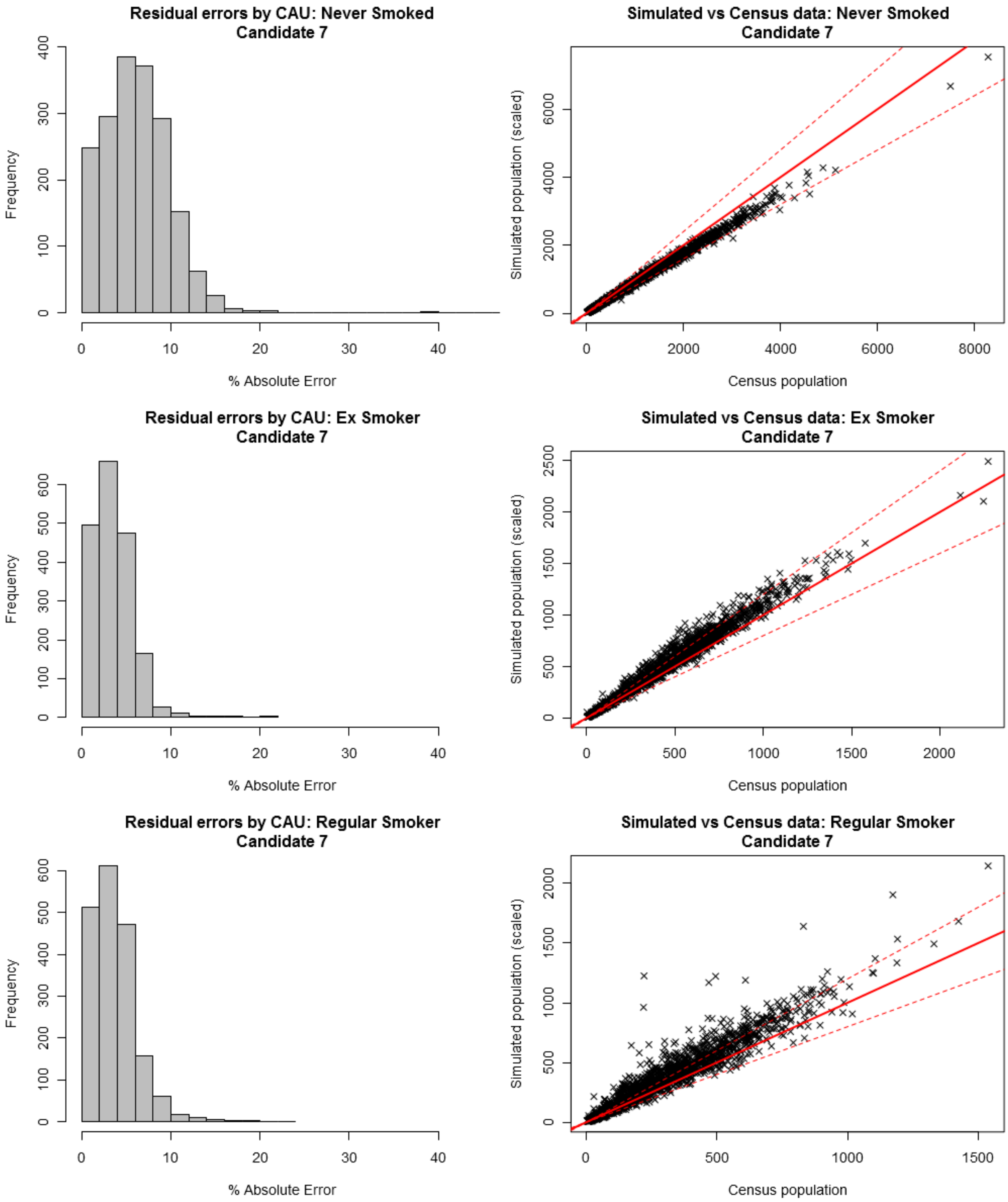


Figure 4.3: External Validation Error for Regular smokers in candidate model 7. Proportional TAE (left) and scaled Census vs simulated data scatter plots (right).

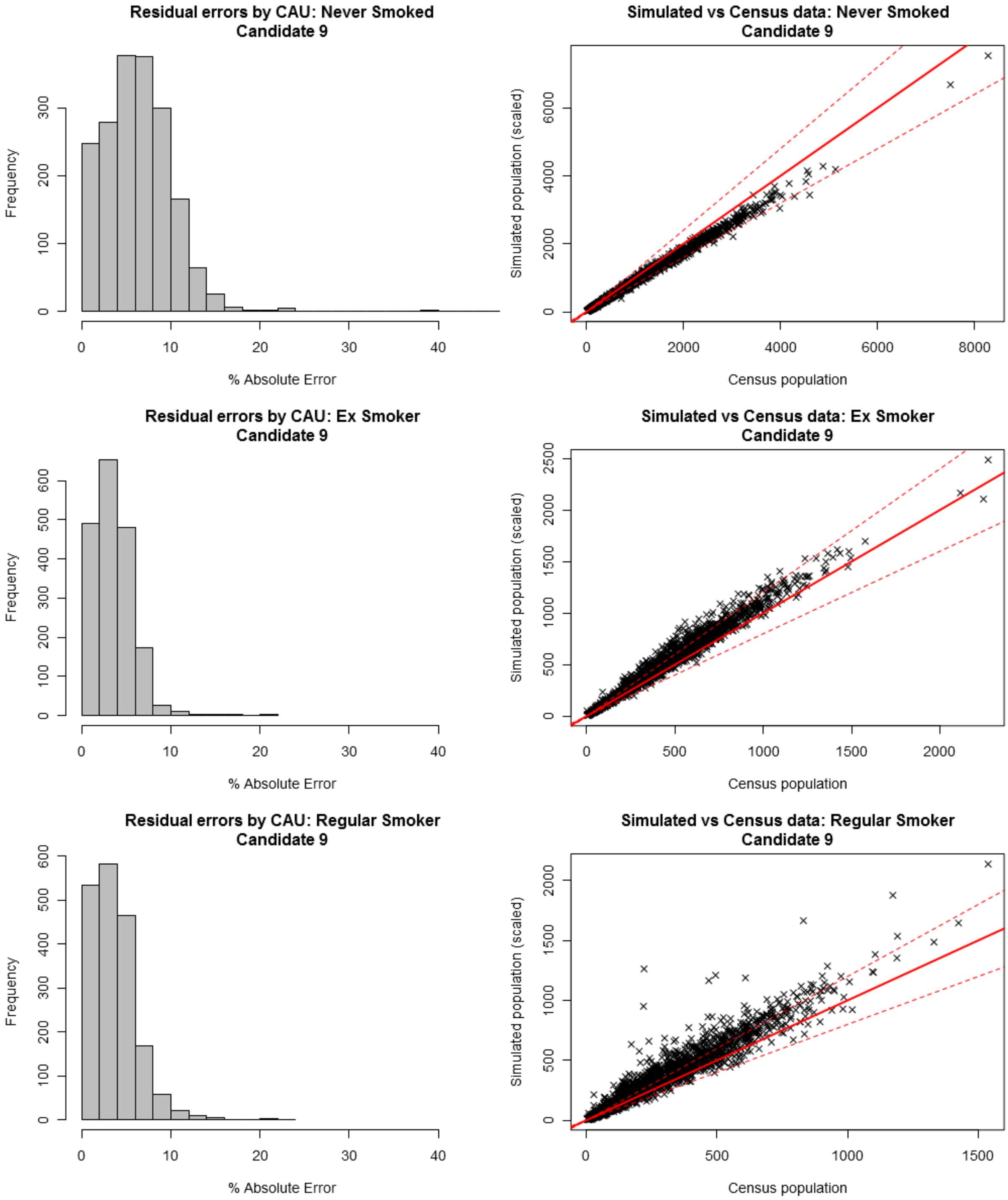


Figure 4.4: External Validation Error for Regular smokers in candidate model 9. Proportional TAE (left) and scaled Census vs simulated data scatter plots (right).

Table 4.15: Differences between the NZHS estimated obesity rate for DHBs and the rate estimated by each candidate model.

	NZHS estimate	NZHS 95% CI	Model 7	Model 9	Cluster model 1	Cluster model 2
National	29.7	29.0–30.4	0.0	0.0	-0.1	-0.1
Auckland	21.8	19.7–24.0	+5.5	+5.4	+5.5	+5.4
Bay of Plenty	31.7	29.5–33.9	+0.4	+0.3	+0.2	+0.2
Canterbury	27.7	25.4–30.1	-1.1	-1.1	-1.2	-1.2
Capital and Coast	25.5	22.5–28.8	+2.1	+2.1	+2.1	+2.1
Counties Manukau	37.7	34.6–40.9	-3.6	-3.6	-3.6	-3.6
Hawke's Bay	33.8	30.8–37.0	-1.0	-1.0	-1.3	-1.3
Hutt Valley	31.0	28.0–34.1	-0.2	-0.3	-0.2	-0.2
Lakes	34.0	31.0–37.1	+0.2	+0.2	+0.1	+0.1
Mid Central	31.4	28.7–34.3	-0.9	-0.9	-1.0	-1.0
Nelson Marlborough	27.5	25.0–30.1	+1.2	+1.2	+0.9	+0.9
Northland	34.1	30.0–38.4	+1.3	+1.2	+1.1	+1.1
South Canterbury	33.1	28.9–37.5	-4.9	-4.9	-5.2	-5.2
Southern	29.4	26.7–32.3	-2.2	-2.3	-2.5	-2.5
Tairawhiti	37.3	33.1–41.7	+0.9	+1.0	+0.7	+0.7
Taranaki	31.5	28.8–34.2	-1.7	-1.7	-1.9	-1.9
Waikato	35.2	32.7–37.8	-4.2	-4.2	-4.3	-4.3
Wairarapa	32.1	27.2–37.5	-1.2	-1.3	-1.5	-1.5
Waitemata	24.3	21.9–26.8	+2.7	+2.6	+2.7	+2.7
West Coast	31.8	27.0–36.9	-2.1	-2.1	-2.5	-2.5
Whanganui	34.5	28.9–40.5	-0.9	-1.0	-1.2	-1.1

Note: NZHS data from Ministry of Health (2015d).

Both models 7 and 9 produced reasonably accurate obesity estimates for most DHBs (Table 4.15), however Auckland was a clear outlier for all models shown in Table 4.15, with estimates around 5.5 percentage points higher than the NZHS estimate, outside the 95% confidence interval for the NZHS estimates. Models 7, 9 produced relatively similar results at DHB level, but Model 7 performed slightly better than model 9 in the external validation results above (see Table 4.14 and Figure 4.3 and Figure 4.4), thus subsequent analyses and results will focus on model 7.

4.3.4 Microdata subsets

A comparison of the results for Tairawhiti and Counties Manukau in Table 4.15 above offers a clue as to why the model fit may be poor for some DHBs. These two DHBs have similar obesity rates (as shown by the NZHS), both have high rates of deprivation, Counties Manukau has large Māori and Pacific populations, and Tairawhiti has a large Māori population. The only major difference between these two DHBs is that Counties Manukau has a large urban population as it covers southern Auckland, whereas Tairawhiti is a remote rural area. Yet, while Tairawhiti is predicted fairly accurately, Counties Manukau is not (estimated obesity rates +0.9 and -3.6 respectively in model 7 compared to NZHS estimates). This suggests that something not captured by the model may be influencing obesity rates.

To test this hypothesis, a model where individuals in the microdata sample were restricted to their 'home' DHB[24] was tested. The problem with doing this is that it reduces the microdata samples available for the SMSM (as low as 608 individuals for Wairarapa DHB). To alleviate this, a third year of microdata was added (two-year sample: 22,461 from 2011-13, three-year sample: 34,955 from 2011-14). Additionally, the DHBs with the worst fit in Table 4.15 were combined with similar DHBs (regardless of validation performance) and three further models created in addition to the DHB model; subsequently these will be referred to as 'restricted' models. The purpose of these three additional models was to combine microdata from similar DHBs together to provide a larger microdata sample, while capturing similar effects to the DHB specific model. The DHB composition of the four restricted microdata models are described in Table 4.16 below along with the available sample sizes. The variable order from model 7 above (sex, age, deprivation, European, Asian, Māori, Pacific, LFS) was used for all of these models. This is similar to a method used by Tanton and Vidyattama (2010) to test the performance of their model; in that example the fit of the model for Australian capital cities was compared using both national and city-specific data.

[24] The 'home' DHB for any given individual is the DHB in which they lived when the NZHS sample was collected. Restricting the micro data sample to their 'home' DHB meant that individuals could only be allocated weights for CAUs within their home DHB. The benefit of this is that individuals are likely to be allocated to areas in which they might realistically live, the main drawback is the reduced sample size as outlined above.

Table 4.16: Summary of restricted data models, including DHBs used to construct these

Model	DHBs used	Average obesity (%)	Sample size	Description
DHB	Every DHB	31.2	608 – 3122	Microdata restricted to their own 'home' DHB.
CITY	Auckland, Waitemata, Capital and Coast	23.9	7783	Highly urban DHBs with low obesity rates
DEP	Counties Manukau, Waikato	36.5	5070	DHBs which contain a major city and also some rural areas. High obesity rates.
RURAL	Counties Manukau, Waikato, Northland, South Canterbury	35.0	7696	Mostly highly deprived, with high obesity rates. Mix of rural and urban DHBs.
FULL	All DHBs	31.3	34955	Standard model 7 with three years of data
STD	All DHBs	30.8	22461	Standard model 7 with two years of data

Table 4.17 summarises which of these restricted microdata models performed best for the DHBs with poor fit in previous validation analyses, assessed against each of the measures used previously. The full analysis of external validation errors is simply too large to present here, it can be found in Table C.5. Because of the size of the original results, Table 4.17 includes only an assessment of which model fits best by which measure for each DHB across the three smoking variables. The results from these models are presented alongside the results from the full 2-year model (STD in this table, model 7 from earlier), and a 3-year version of the same model (FULL)

Most of the restricted microdata models showed better performance than the full model. Auckland showed the greatest success with the DHB-only model, but the slightly less well performing CITY model has been used due to the small microdata sample size. The selected model for each of these DHBs is also indicated in Table 4.17. For DHBs not shown here, the FULL, 3-year model was used as the default. The full analysis of all models in Table 4.17 is available in Appendix C as the table is too large to include in the main text. The final estimates and errors are shown in Table 4.18; these are within the NZHS's 95% confidence interval except for Auckland DHB.

Table 4.17: Summary of restricted microdata model performance across key accuracy measures

		Difference (3 years of data unless specified)												
	NZHS	**STD 2 year**	**FULL 3 year**	**DHB**	**CITY (low)**	**DEP (high)**	**RURAL (high)**	**DHB Sample size**	**Selected model**	**DHB errors favour**	**Spread favours**	**Std Errors favour**	**Means & medians favour**	**TAE favours**
National	29.7	-0.0	+0.4	+0.4	-1.7	+3.5	+3.0	34,955	NA	STD	Various	DEP	DEP*	STD*
Auckland	21.8	+5.5	+5.9	+1.5	+3.8	NA	NA	2,823	CITY	DHB	STD	CITY	CITY	DHB*
Capital and Coast	25.5	+2.1	+2.5	+0.6	+0.1	NA	NA	2,108	CITY	CITY	Various	CITY	CITY	DHB
Counties Manukau	37.7	-3.6	-3.1	+0.5	NA	-0.4	-0.8	2,823	DEP	RURAL	FULL	DEP	DEP	DEP
Northland	34.1	+1.3	+1.9	NA	NA	NA	+3.7	1,772	FULL	STD	RURAL	RURAL	RURAL	RURAL
South Canterbury	33.1	-4.9	-4.4	NA	NA	NA	-1.9	854	RURAL	RURAL	RURAL	RURAL	FULL	FULL
Southern	29.4	-2.2	-1.8	-0.7	NA	NA	NA	2,526	FULL	DHB	Various	STD	STD	FULL
Waikato	35.2	-4.2	-3.7	-1.8	NA	-0.7	-1.4	2,247	DEP	DEP	RURAL	DEP*	DEP	DEP
Waitemata	24.3	+2.7	+3.1	+3.1	+0.7	NA	NA	2,852	CITY	CITY	FULL	CITY	CITY	CITY

Notes: results marked with an * indicate models that are strongly preferred by this measure.

Table 4.18: DHB level obesity estimates and difference from NZHS for both the full model 7 (3 year) and the combined restricted data model

			Estimated obesity		Estimated error	
	NZHS	NZHS 95% CI	FULL 3y model	Restricted model	FULL 3y model	Restricted model
National	29.7	29.0–30.4	30.1	30.1	0.4	0.4
Auckland	21.8	19.7–24.0	27.7	25.6	5.9	3.8
Bay of Plenty	31.7	29.5–33.9	32.6	32.6	0.9	0.9
Canterbury	27.7	25.4–30.1	27.0	27.0	-0.7	-0.7
Capital and Coast	25.5	22.5–28.8	28.0	25.6	2.5	0.1
Counties Manukau	37.7	34.6–40.9	34.6	37.3	-3.1	-0.4
Hawke's Bay	33.8	30.8–37.0	33.3	33.3	-0.5	-0.5
Hutt Valley	31.0	28.0–34.1	31.2	31.2	0.2	0.2
Lakes	34.0	31.0–37.1	34.8	34.8	0.8	0.8
Mid Central	31.4	28.7–34.3	31.0	31.0	-0.4	-0.4
Nelson Marlborough	27.5	25.0–30.1	29.2	29.2	1.7	1.7
Northland	34.1	30.0–38.4	36.0	36.0	1.9	1.9
South Canterbury	33.1	28.9–37.5	28.7	31.2	-4.4	-1.9
Southern	29.4	26.7–32.3	27.6	27.6	-1.8	-1.8
Tairawhiti	37.3	33.1–41.7	38.9	38.9	1.6	1.6
Taranaki	31.5	28.8–34.2	30.3	30.3	-1.2	-1.2
Waikato	35.2	32.7–37.8	31.5	34.5	-3.7	-0.7
Wairarapa	32.1	27.2–37.5	31.3	31.3	-0.8	-0.8
Waitemata	24.3	21.9–26.8	27.4	25.0	3.1	0.7
West Coast	31.8	27.0–36.9	30.2	30.2	-1.6	-1.6
Whanganui	34.5	28.9–40.5	34.2	34.2	-0.3	-0.3

4.3.5 Validation of the final model

When the selected restricted models were combined as above, the validation results at a national level were better than for the full model on its own (see Table 4.19). The combined restricted data model, when compared with the best single model had slightly higher spread between the mean and median values, but has lower mean and median errors (particularly for those who have never smoked), much lower standard errors, and lower total error. The highest SAE in the combined model was found for those who had never smoked. Ex-smokers and regular smokers had lower maximum error values, but more dispersion from the Census data. Table 4.19 also gives the percentage of areas with SAE greater than both 10% and 20% for each validation variable across both the restricted data and FULL models. Ideally, no more than 20% of areas should have SAE over 20%, though Smith et al. (2011) also uses a 10% threshold (in 90% of areas) as a more rigorous measure. The 10% threshold clearly indicates that the model predicts those who have never smoked less well than smokers or ex smokers. The external validation errors (SAE) are also shown in histogram form alongside a scatter plot of the simulated data against scaled Census data (scaling accommodates non-response, as discussed in Sub-section 4.3.3) in Figure 4.5, which can be compared with the earlier Figure 4.3.

The areas with >20% SAE in any one of the smoking categories fell into three groups. The first of these had very high student populations (total usually resident population >3000), all of which were around the University of Otago in Dunedin (Stuart St-Frederick St, North Dunedin, and Otago University). The second group of high error areas had very small populations (Haupiri, Hyde, Sandymount and Silverstream), the largest of which was Haupiri with a usually resident population of 249. The final area with high error was Temple View, this is an area with a high Mormon population, and as such, the number of smokers (and alcohol consumption) is likely to be lower than might be expected based on its demographics.

Table 4.19: External validation for the combined restricted data model and standard model 7 (3 years of data).

	Combined restricted data model			**FULL model (3 years of data)**		
	Never	**Ex**	**Regular**	**Never**	**Ex**	**Regular**
Mean	5.60	3.31	3.29	6.18	3.50	3.59
Median	5.36	3.06	2.86	6.00	3.29	3.23
Spread	0.24	0.26	0.43	0.18	0.21	0.36
Std Error	2.78	1.43	1.82	3.10	1.51	2.05
Minimum	0.00	0.01	0.00	0.00	0.00	0.00
Maximum	39.22	21.59	21.57	40.68	21.59	23.05
TAE	201,023	107,016	109,743	227,530	116,244	125,344
% SAE >20%	0.38	0.11	0.11	0.43	0.11	0.11
% SAE >10%	10.11	1.24	2.06	13.95	1.19	2.33

Note: Numbers refer to SAE values unless otherwise specified.

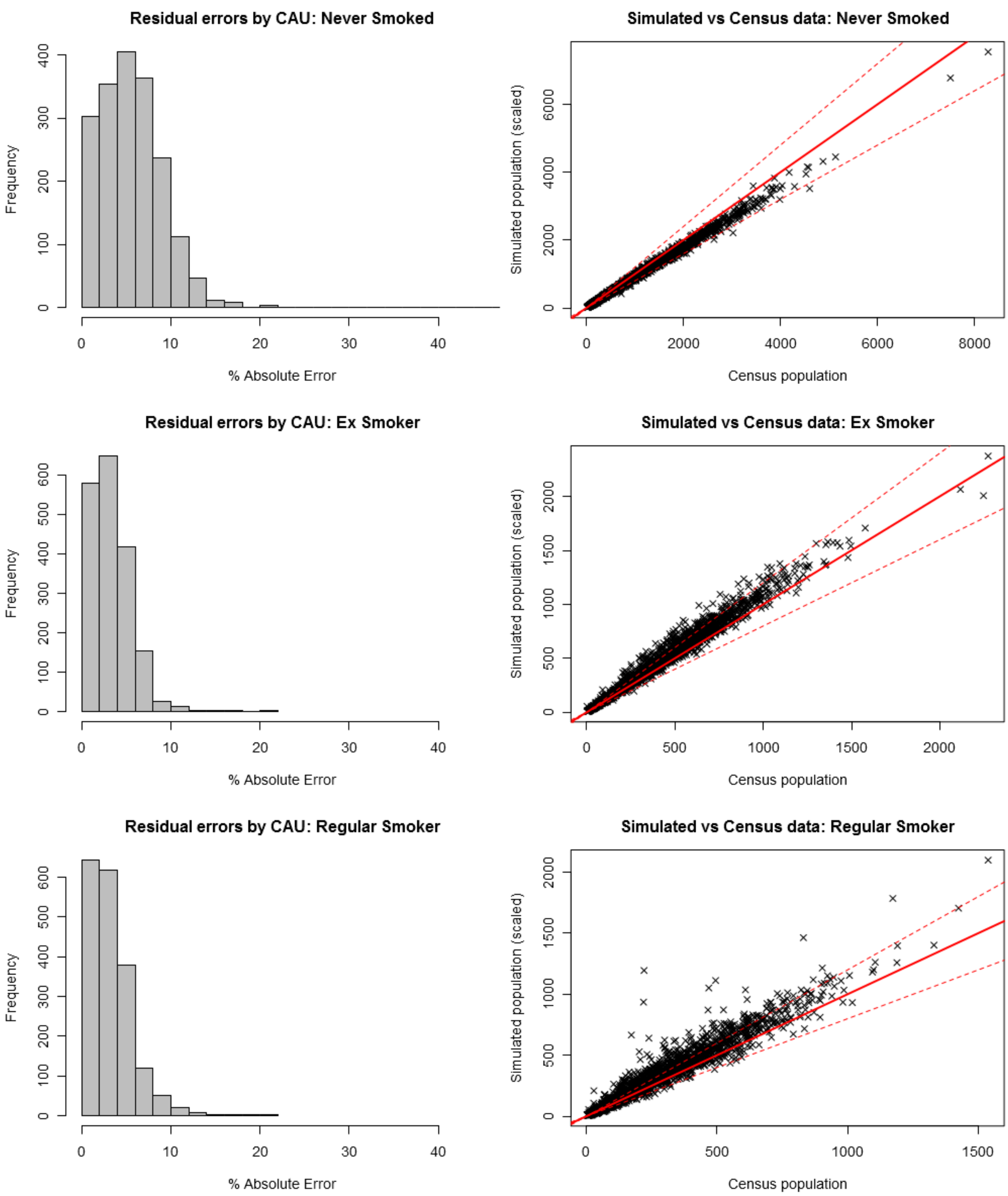


Figure 4.5: Overall external validation error by CAU for the final model. Proportional TAE (left) and scaled Census vs simulated data scatter plots (right).

Percentage estimates of regular smokers from the SMSM were also compared to the same data from the Census. SMSM estimates of smoking rates were generally slightly higher than the Census data for the same CAU, see Figure 4.6 below. This view of the validation data shows the errors in the model relative to the smoking rate, and shows somewhat higher dispersion around the 1:1 line of best fit than the absolute population plot in Figure 4.5.

Figure 4.6 also includes labels for the high error areas mentioned earlier in this section; note that some areas have small errors in this figure because not all areas had high error for this variable — regular smokers.

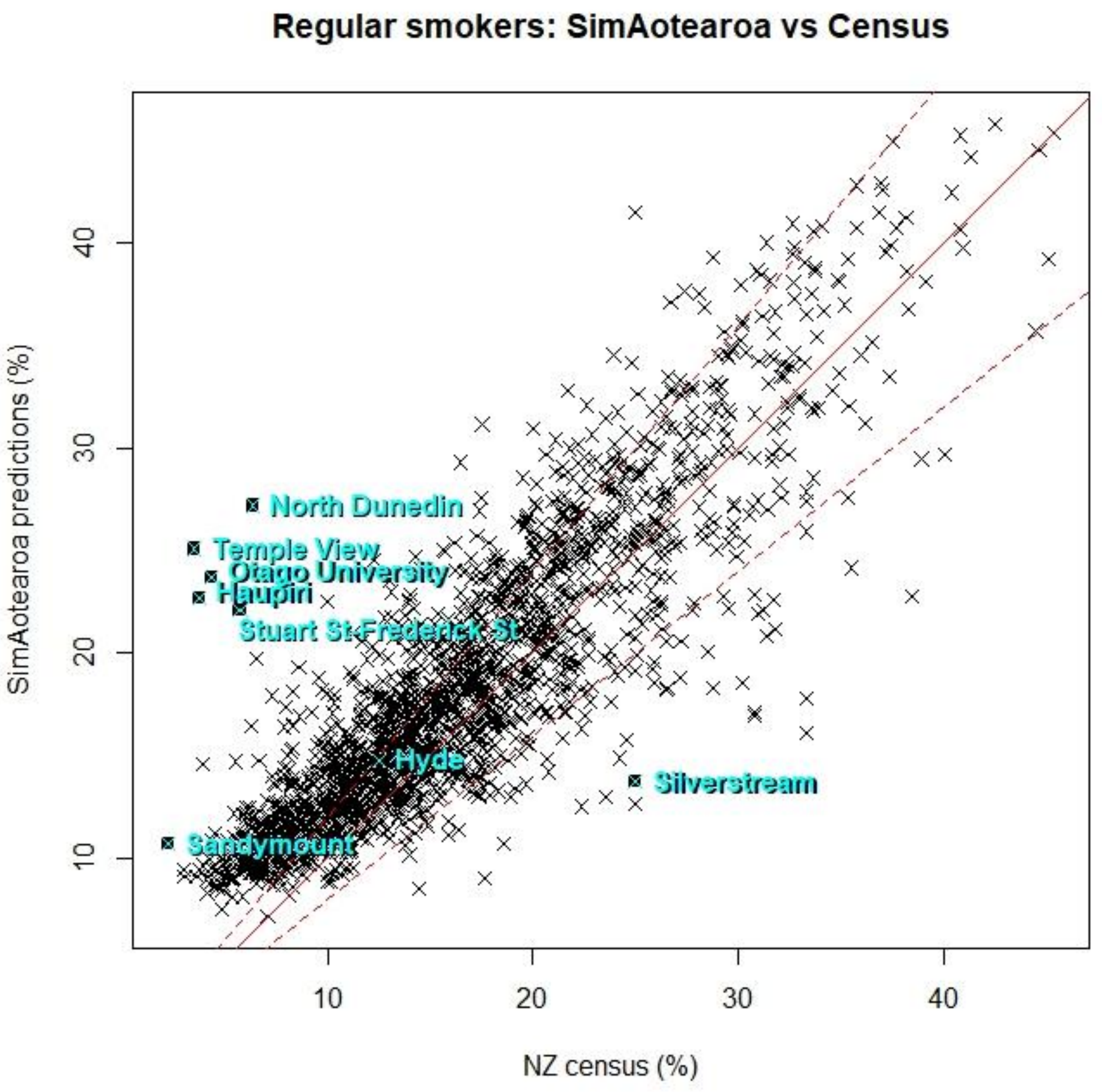


Figure 4.6: SMSM vs Census percentages for regular smokers[25].

Because the Census categories are mutually exclusive, the validation maps (Figure 4.7) show reversed patterns. The never smoked maps (Figure 4.7) are close to the exact inverse of the regular smoker maps (Figure 4.9), with the ex smoker maps (Figure 4.8) falling somewhere

[25] Note that all of the locations highlighted in this figure are in areas (e.g. Dunedin) not readily visible on the maps used in this thesis.

in between, though they were most similar to the regular smoker maps. Rates of those who had never smoked (Figure 4.7) tended to be underestimated in wealthy urban areas (e.g. central Auckland, Wellington city, or western Christchurch), and overestimated in some rural areas, most notably the West Coast. Rates of smokers (Figure 4.9) were underestimated in rural areas and overestimated to the greatest extent in wealthy urban areas. Maps showing the clustering of the validation variables using Moran's *I* are available in Appendix C.

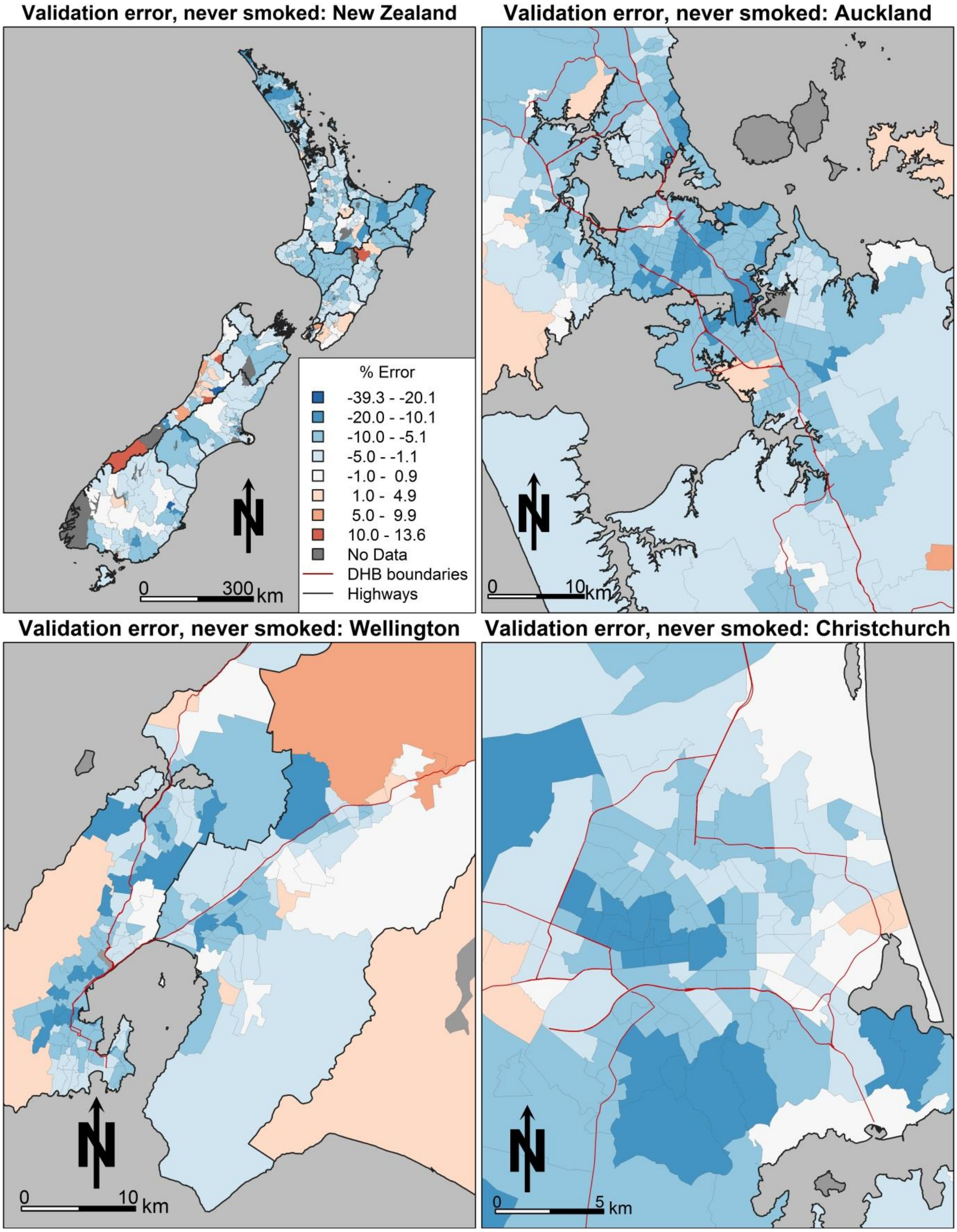


Figure 4.7: Mapped External Validation error by CAU for those who have never smoked

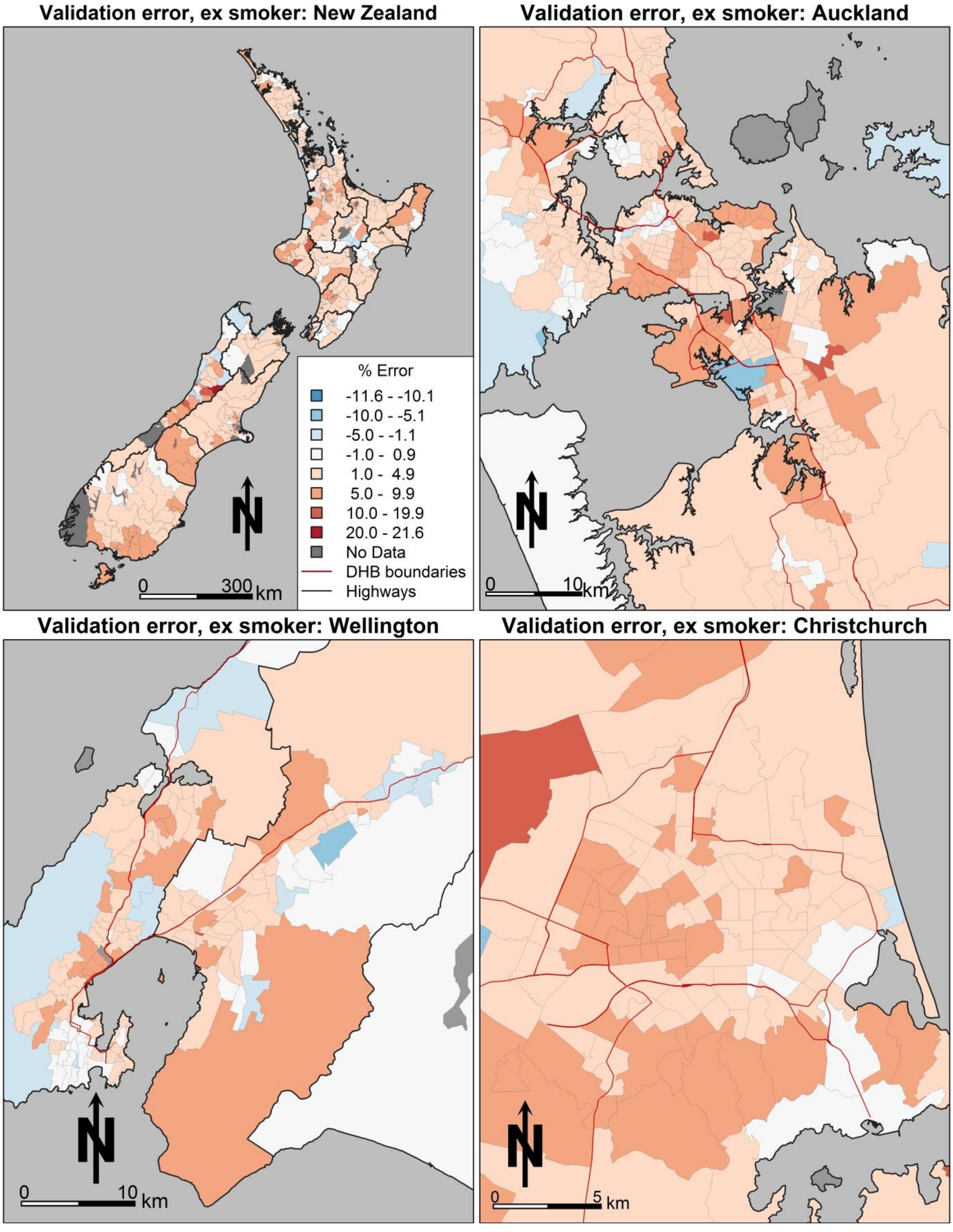


Figure 4.8: Mapped External Validation error by CAU for Ex smokers

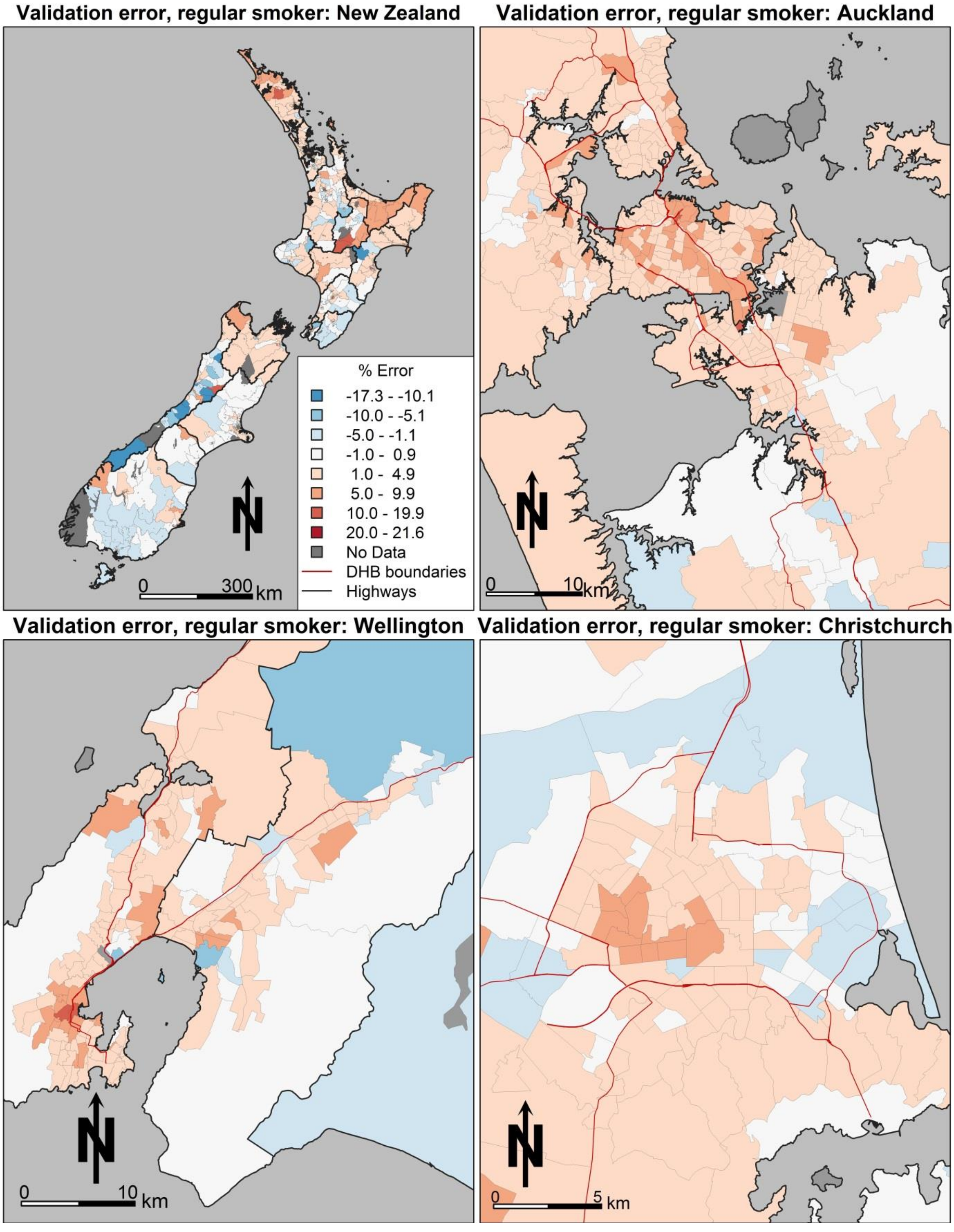


Figure 4.9: Mapped External Validation error by CAU for Regular smokers

4.4 Discussion of the model design and validation

The previous section presented the model construction process and established the validity of the SimAotearoa model. The purpose of this section is to assess the construction and validation performance of SimAotearoa in comparison to existing models. This section will cover: the limitations of SimAotearoa, and the challenges posed by the data available for current Census geographies (Sub-section 4.4.1), an assessment of the validation process and comparison to other similar models (Sub-section 4.4.2), and discuss in more detail the use of microdata in the model (Sub-section 4.4.3).

4.4.1 Model geography and limitations

The key limitation of SimAotearoa is that it is a statistical representation of the real world and will necessarily contain a degree of inaccuracy. Though the model is robust, it is not perfect. The modelled estimates are generated through real survey and Census data, but these were not drawn from every small area. Thus, estimates for some areas are based on data not from that area, unlike in a regression or Bayesian model which requires data for every area. This is also one of SMSM's strengths, it can provide an estimate where a more conventional modelling technique could not.

The geographic scale of the model caused some difficulty during the model building process. SimAotearoa has been constructed at a CAU scale, but many of these areas had heterogeneous populations and the model could not readily distinguish among them. The large population size and geographic area of many CAUs is partially responsible for this (see Sub-section 4.2.1 for a discussion of the relative size of this areal unit compared to international examples). However, the primary problem is that CAU populations are relatively heterogeneous, as demonstrated by the *D*-statistic results in Table 4.8, which indicated all variables except deprivation and ethnicity were mixed throughout CAUs. This heterogeneity made it difficult to construct a model with the ability to distinguish between different types of areas. This is particularly apparent in Central Auckland, where the SMSM result that most closely matched the NZHS estimate was produced from microdata restricted to this region. Despite these limitations, CAUs were used for this model as the only smaller area available, MBs, had many confidentialised constraint table cells (cells with no data) due to their small size and thus did not provide adequate data integrity.

Smaller Census geographies may offer a finer scale picture of obesity than is possible with the geographic scales available for use in SimAotearoa. Exeter et al. (2017) describe the development of 'Data Zones,' a geography intermediate in size between MBs and CAUs, which has proved a useful scale for geographic research and which may be desirable for SMSM (see also Zhao & Exeter, 2016). There was no intermediate Census geography available between MBs and CAUs for 2013 Census data at the time this research was conducted. However, the updated *Statistical standard for geographic areas 2018* (Stats NZ, 2017b) replaces MBs with the slightly larger SA1 areas and CAUs with the slightly larger but more standardised SA2, which will impact on their use for SMSM. The new SA1 areas may be large enough to avoid the confidentiality issues that prevented the use of MBs in SimAotearoa; smaller areal units offer greater likelihood of population homogeneity within the unit, and this is a desirable characteristic for SMSM. The concern with using a smaller geographic scale is that the deprivation data used in SimAotearoa relies on using deprivation data at two spatial scales, which may not be possible with either Data Zones or the new SA1 and SA2 geographies. The indices of multiple deprivation (IMD), a composite index able to be decomposed into its constituent parts and developed using the Data Zones may offset this concern (Exeter et al., 2017). The new statistical standard also includes an updated urban/rural classification which may offer a different method of generating microdata subsets in future (Stats NZ, 2017b).

4.4.2 Comparison to other models

Against the methods outlined in Section 4.1, the validation presented here has focused on using TAE at national scale, and SAE at small area scale. These measures were used to compare model estimates to both internal (constraint) and external (Census smoking) data. In addition, obesity estimates were aggregated to DHB level and compared to estimates obtained using the NZHS data set with standard statistical methodology. Aggregation to DHB level showed that SimAotearoa produces reasonable obesity estimates at DHB scale with all estimates other than Auckland DHB being within the 95% CI for the NZHS estimate.

SimAotearoa can be considered robust when it is compared with other similar models. Smith et al. (2011) used a SMSM based on data from Aotearoa New Zealand to test the accuracy of SMSM predictions, in comparison to this, SimAotearoa has improved slightly on the fit of the SMSM when comparing percentage of regular smokers with Census results (Figure 4.6). The range of fitted results in SimAotearoa is more centred around the 1:1 relationship line, this can be seen in the greater clustering of errors around zero in Figure 4.6, as well as the percentage of areas with SAE under 10% —in SimAotearoa this was 97.9% in comparison to 75.3% in Smith et al. (2011). SimAotearoa also better reflects recent changes in the collection of Census data as Smith et al.'s (2011) model was built using 2006 Census data and prioritised ethnicity (see the discussion in Sub-section 4.2.3 about types of ethnicity data).

It would be ideal to use a fully external data set for validation, one originating from a separate source to the two data sets used to build the model, as described by Edwards and Tanton (2013). Edwards et al. (2011) used a much more rigorous external validation methodology to validate the adult version of SimObesity — comparing modelled obesity estimates to rates of cancer associated with obesity, and this is clearly the best standard for SMSMs built to estimate obesity. However, other published models use weaker validation with limited or no external validation (Cataife, 2014; Koh et al., 2015), this also includes the child version of SimObesity due to the study area not matching available data geographies (Edwards & Clarke, 2009). Despite the lack of validation using a separate data set, validation using unconstrained small area Census data for a health related variable (smoking) is clearly considered an important check of model accuracy (Smith et al., 2011), and the model can be considered to perform well in comparison to other comparable SMSMs.

4.4.3 Microdata selection

The restriction of the microdata sample used in some regions is a key feature of SimAotearoa. There is some disagreement among the literature as to whether this is beneficial. A number of published models (including obesity models) use microdata samples that are specific to the study region. For example, Hermes and Poulsen (2012a) used microdata restricted to Greater London to build a SMSM for smoking in that city, Anderson (2013) used a subset of microdata specific to the study region (Wales) for assessing income deprivation, Ballas et al. (2007a) used data from the Yorkshire and Humber region to simulate socio-economic impacts of national policies in the city of York, Koh et al. (2015) used microdata specific to the study area (Detroit Tri-County Metropolitan Area) to model obesity, and Cataife (2014) used a state level subset of a national microdata set to build a city specific model for obesity in Rio de Janeiro. Conversely, Edwards and Clarke (2013) prefer a larger, non-restricted, microdata sample for their model of obesity in northern England.

Birkin and Clarke (2012) discuss models which produce results that look 'flat': they identify over-replication of 'average' households or individuals as a cause of this flattening of the results. Edwards and Clarke (2013) take this further and link it to the size of the microdata set — a smaller data set is less likely to have ‘uncommon’ households or individuals, thus the model has fewer unusual samples to select among and is likely to misestimate these depending on whether or not they match a given area.

Yet in SimAotearoa, it was the overestimate of the ‘*average*’ household in unusual regions that is most likely to have driven the inaccuracy of the initial results, and thus the decision to use restricted microdata sample. The lack of fit in some parts of the DHB model were more likely due to the absence of certain groups in small DHBs (causing mathematical errors), than simply an insufficient population for the modelling process to find suitable matches. A pattern similar to this can be seen in Anderson, De Agostini, and Lawson (2012), where they were not able to detect an expected effect in rural areas.

Only two papers could be found that tested the impact of microdata selection on the model outputs. Hermes and Poulsen (2012b) tested the impact of microdata samples by creating two models based on different surveys and found this had a noticeable impact on the results. Conversely, Tanton and Vidyattama (2010) found that restricting the microdata to individuals only from major cities had only limited impact — influencing smaller cities but not large ones — compared with using the whole microdata set . This is similar to the CITY model described above, but somewhat different to the DHB model. Tanton and Vidyattama (2010) used a different microsimulation methodology (GREGWT) to SimAotearoa, and the validation methodology they used is very different, limiting comparisons.

Based on the difficulties experienced in fitting this model, the degree of heterogeneity in the outcome variable among regions (whether they are health boards, cities, or rural areas) is an important factor in model composition. Based on these results, high heterogeneity in a large study area suggests a need to ensure that individuals from the microdata are used for simulation in areas which are most similar to their home location. Where there is significant heterogeneity among regions in a large study area, it may be beneficial to test models using subsets of the microdata sample in the SMSM. Unlike in the analysis conducted by Smith et al. (2009), grouping Census areas into clusters did not improve the fit of SimAotearoa. Based on this experience, it can be inferred that the clustering method cannot help if the differences between areas are not reflected in the candidate models.

The restricted data model was developed as a compromise between the fully national, or fully DHB restricted models. The success of the restricted model demonstrates that individuals in some areas are unlike ostensibly similar individuals (in terms of model parameters) that live elsewhere in Aotearoa New Zealand. These differences were particularly apparent in Central Auckland, where the fit of the FULL model was the worst. The differences in how well each type of model fits may be a result of differences in demographic composition (Smith et al., 2009), though what might cause this is difficult to tease out from the available data. It is more likely that these differences arise through factors that cannot be modelled, such as city-level transport practices, differences in behaviour between rural and urban populations, or at the neighbourhood level the presence or absence of local amenities.

Birkin and Clarke (2012) addressed the issue of un-modellable heterogeneity by restricting microdata not to their ‘home’ region, but to their geodemographic grouping. Aotearoa New Zealand lacks a well-recognised geodemographic classification system such as the Output Area Classification (OAC) used in the UK (Vickers, Rees, & Birkin, 2005). However, the use of deprivation functioned, incompletely, in a similar way within the model. No attempt was made to construct a geodemographic classification for Aotearoa New Zealand for two practical reasons: time constraints, and the size and heterogeneity of CAUs. However, the primary reason is because the spatial segregation of ethnicity and SES in Aotearoa New Zealand would likely mean that this type of classification would replicate existing structural inequities.

The restricted data model was an attempt to utilise the strengths of the geodemographic method without needing to classify individual area units. It is similar to the work of Tanton and Vidyattama (2010), described earlier in this section. Tanton and Vidyattama (2010) proposed that estimates for areas with a small sample size would be more accurate if restricted to that small sample, but that restriction would have little effect on areas with larger sample sizes; the results presented in this chapter are not consistent with this conclusion. Although the error rates for several small DHBs improved using a DHB specific model, errors became worse in others (consider the standard errors for Tairawhiti given in Table C.5). The behaviour of SimAotearoa is much more consistent with Birkin and Clarke’s (2012) discussion of un-modellable factors and use of geodemographics, than Tanton and Vidyattama’s (2010) sample size theory.

4.5 Summary: Technical advances

The purpose of this chapter was to address Objective 2: to develop a spatial microsimulation model (SimAotearoa) suitable for estimating adult obesity and diabetes at a small area level in the Aotearoa New Zealand population in 2013; and to test the validity of this model.

This chapter has demonstrated SimAotearoa to be robust in comparison to regionally aggregated obesity data from the NZHS and small area smoking data from the Census. It meets the accepted criteria for SMSM accuracy, with very few areas exhibiting greater than 20% error in any validation analysis. Further, SimAotearoa performed better than the only prior SMSM produced in Aotearoa New Zealand, which was held to demonstrate the robustness of the method for producing health related estimates (Smith et al., 2011).

The key contribution of SimAotearoa to the SMSM literature in terms of the technical details of model construction is the use of multiple subsets of microdata to build a cohesive model for obesity that is intended for policy use. Other work has tested the impact of microdata subsets, but found them to be of benefit only in limited situations (Tanton & Vidyattama, 2010). In doing so, SimAotearoa contributes to the discussion in the literature surrounding the causes of under-differentiated estimates among areas and the selection of microdata samples for SMSM. Other novel features of SimAotearoa include the construction of the deprivation variable used, and the use of total response ethnicity, both of which were responses to unique Aotearoa New Zealand data.

Two findings of consequence for the development of SMSMs in Aotearoa New Zealand and in general have been discussed in this chapter. Firstly, where there is significant heterogeneity in the outcome variable among regions it may be beneficial to test models using subsets of the microdata sample in the SMSM. Depending on the data available, this may be restricting the microdata to their ‘home’ region, or grouping the microdata from several similar regions (e.g. cities) together to produce a larger sample. Secondly, the size of the areal unit used as the basis of a SMSM model is important. Too small, and the data contain too many confidentialised cells and are of insufficient quality to construct a meaningful model. Too large and the constituent population becomes homogenised and difficult to differentiate from other areas. Future SMSMs in Aotearoa New Zealand should ideally utilise the new SA1 areas, depending on the impact of the deprivation variable.

Chapter 5 Obesity in the ‘hood? Spatial patterning of obesity and related measures

Chapter 4 outlined how SimAotearoa was designed, built, and validated. In this chapter, the small area obesity estimates generated by SimAotearoa are presented and evaluated. In addition, estimates for key sub population groups will also be examined, along with the implications of the results.

This chapter addresses the static portion of Objective 4: to explore the results of both static and projected spatial microsimulation models for obesity, diabetes, and key population subgroups, including how these results may be potentially relevant to policy. The results presented here are drawn directly from the model designed and validated in Chapter 4, thus most of the results included here are maps produced using methods that have already been discussed in the previous chapter, or tabulations of those results. Consequently, no separate methods section has been included in this chapter.

Section 5.1 introduces and describes previous SMSMs focussing on obesity. The results from SimAotearoa will be presented in Section 5.2, including DHB level estimates of obesity as well as CAU estimates for the whole population for obesity, combined obesity and overweight, and diabetes. Section 5.2 also includes subpopulation results for obesity, along with several analyses of the results. Section 5.3 will discuss these results within the international context, spatial segregation of obesity rates among CAUs, and the limitations of this work. Finally, the chapter will be summarised in Section 5.4.

5.1 Review of previous obesity spatial microsimulation models

SMSM was first introduced in the literature review, along with its use for policy analysis and examples for public health purposes (Section 2.4). The purpose of this section is to outline some of the results found by previous models focussing on obesity so that the results of SimAotearoa can later be viewed within their international context.

Six previous studies have used SMSM to investigate obesity. Each was constructed and the results analysed using differing methods, but most selected a deterministic algorithm for the

SMSM. The earliest examples were produced by Kimberley Edwards[26] and colleagues (Edwards & Clarke, 2009, 2013; Edwards et al., 2011; Procter et al., 2008) and use the SimObesity model to investigate obesity in England; two of these papers relate to children, and two to adults. The papers relating to children are based in Leeds and more concerned with the relationship between obesogenic environmental factors and childhood obesity than estimating obesity rates per se (Edwards & Clarke, 2009; Procter et al., 2008), though Procter et al. (2008) estimated that childhood obesity among areas in Leeds varied between 1.4% and 16.0%. Both papers also noted an association between deprivation and obesity, but that this was non-stationary and varied with other factors; in some places affluence was associated with obesity, perhaps through more sedentary behaviour. The two SimObesity papers relating to adults focused on a larger region of Northern England (Edwards & Clarke, 2013; Edwards et al., 2011). These found obesity rates between 14% and 31% (2011), though both of these papers were more focussed on methods than results.

Conditions for the development of obesity differ between developing and developed countries, with many developing countries experiencing both under and over nutrition (Popkin, 2001; Popkin et al., 2012). This can be seen in the model constructed by Cataife (2014), who has produced the only obesity SMSM model so far designed for a developing country (Brazil). This was the only model that used a stochastic simulation method. Cataife (2014) estimated that obesity rates in Rio de Janeiro varied between 0% and 42.9%, and investigated relationships with obesogenic factors such as sugary drink consumption. Cataife (2014) found some evidence for the dual burden of obesity and underweight that is sometimes found in developing countries (Popkin et al., 2012), but not for all areas.

Koh et al. (2015) found obesity rates ranging from 21.5% to 56.9% in Detroit in the USA, as well as a strong correlation with low income. They also found some evidence of a correlation between obesity and unhealthy food; however, they could not find a relationship between obesity and food deserts. The model did not fit as well in low obesity areas, which was also a problem during this study (see Sub-section 4.3.4).

Another SMSM study that included obesity was Campbell and Ballas (2016). However, in this study obesity was one of several variables included and no specific values were reported.

[26] Née Procter.

5.2 Main results

The previous section outlined the findings of prior SMSM models focusing on obesity internationally. This section presents a detailed description of the results of the SMSM model, at CAU and DHB scales for the whole population and for key subpopulations for Aotearoa New Zealand.

The analyses presented below are in five sections. First, a summary of estimated obesity, overweight, combined obesity and overweight, and diabetes by DHB and CAU (Sub-section 5.2.1). Second, maps showing the prevalence of obesity (both BMI and waist measurement), severe obesity, combined overweight and obesity, and diabetes (Sub-section 5.2.2). Third, a more detailed analysis of obesity estimates including cluster analysis and interaction with deprivation, severe obesity and diabetes (Sub-section 5.2.3). Fourth, maps for population subgroups: Māori, Pacific, Asian, European, young (age 15-24), Male, Female, and an example of combining subgroups to identify "high risk" areas (Sub-section 5.2.4). Fifth and finally, comparisons showing the distribution of estimates for different deprivation categories or DHBs across several variables and subpopulations: obesity, combined obesity and overweight, diabetes, Māori, Pacific and young people (Sub-section 5.2.6).

5.2.1 Estimated obesity prevalence in the final model

The first part of the analysis examined rates of obesity and related measures for the whole population at both DHB and CAU scale. Estimates of obesity (using both BMI and waist measurements), overweight, combined obesity and overweight, and diabetes were extracted from the SMSM and aggregated for each DHB and nationally (see Table 5.1). Auckland, Waitemata, and Capital and Coast DHBs had estimates at least 4% below the national estimate across all measures except diabetes —obesity (both measures) and combined obesity and overweight. Canterbury DHB also had estimates consistently below the national average, but to a lesser degree (around 2%). Counties Manukau, Lakes, Northland, Tairawhiti, Waikato and Wanganui all had estimates at least 4% above the national average across the same measures. Hawke's Bay and Bay of Plenty DHBs also showed estimates above the national average across the same measures, but to a lesser degree (around 2-3%). As will be seen again later in this section, overweight alone showed the opposite pattern, this is likely because the obese and overweight categories are mutually exclusive. For example, it is mathematically impossible for an area to exhibit both 60% obesity and 60% overweight because this sums to greater than 100%. All diabetes estimates were close to the national average of 5.7%, though they were slightly higher (up to 2%) in the areas of high obesity listed above.

Table 5.1: DHB level estimates for rates of obesity, overweight and diabetes, with NZHS obesity estimates for comparison

Percent	NZHS obese	Obese (BMI)	Obese (waist)	Overweight	Overweight and obese	Diabetes
National	29.7	30.0	36.9	34.3	64.3	5.7
Auckland	21.8	25.6	30.9	32.8	58.5	5.5
Bay of Plenty	31.7	32.6	40.8	34.9	67.5	6.6
Canterbury	27.7	27.0	34.3	36.2	63.1	4.6
Capital and Coast	25.5	25.6	31.3	34.2	59.7	4.5
Counties Manukau	37.7	37.3	42.7	31.1	68.5	7.3
Hawke's Bay	33.8	33.3	41.1	34.7	68	6.4
Hutt Valley	31.0	31.2	37.8	34.6	65.7	5.6
Lakes	34.0	34.8	41.8	34.0	68.8	6.6
Mid Central	31.4	31.0	38.6	34.5	65.5	5.9
Nelson Marlborough	27.5	29.2	37.7	36.7	65.9	5.4
Northland	34.1	36.0	44.0	33.9	69.9	7.7
South Canterbury	33.1	31.2	39.5	36.0	67.3	5.3
Southern	29.4	27.6	35.1	35.9	63.5	4.7
Tairawhiti	37.3	38.9	45.5	32.6	71.4	7.7
Taranaki	31.5	30.3	38.1	35.7	66	5.5
Waikato	35.2	34.5	42.0	33.5	68	6.0
Wairarapa	32.1	31.3	39.8	35.8	67.2	6.1
Waitemata	24.3	25.0	31.3	34.3	59.4	5.0
West Coast	31.8	30.2	38.1	36.2	66.4	5.4
Whanganui	34.5	34.2	42.3	34.3	68.5	6.9

Next, CAU level estimates of obesity, overweight, combined obesity and overweight and diabetes were extracted from the SMSM and summary statistics calculated (see Table 5.2). Estimated obesity rates range between 15.3% and 67.2% using BMI, and between 19.1% and 64.2% using waist measurements. Obesity based on waist measurements was much higher overall, but with a similar spread of values. The range estimated rates of overweight is much smaller, from 20.2% to 42.2%, and more clustered around the mean (the interquartile range was 4.1%, compared with 9.0% for obesity). As mentioned above, this is likely because combined obesity and overweight categories are mutually exclusive, thus areas with high obesity must necessarily have somewhat lower rates of overweight. This mathematical cap on rates of overweight can be seen in Figure 5.1 where the overweight graph stops abruptly at around 40%.

Table 5.2: Summary of CAU level obesity, overweight, and diabetes estimates for the final model

Percent	**Obese (BMI)**	**Obese (waist)**	**Overweight (BMI)**	**Overweight and obese**	**Diabetes**
Minimum	15.29	19.06	20.19	41.18	0.82
Lower Quartile	25.32	32.55	33.07	62.41	4.00
Median	29.40	37.00	35.29	65.59	5.22
Mean	30.77	37.76	34.75	65.52	5.69
Upper Quartile	34.30	42.15	37.20	68.50	6.91
Maximum	67.16	64.19	42.25	87.83	15.68

Some notable patterns were also found in the combined obesity and overweight data. The rate of combined obesity and overweight ranged from 41.2% to 87.8%, with an interquartile range in between that of either obesity or overweight alone (6.1%). Also of note is that the highest estimated combined rate for a CAU was 87.8%. Young people and older people (over 60) are well known to have lower BMI values and thus obesity rates (Elia, 2001; Ministry of Health, 2015a). Consequently, all areas will have a portion of people who are of normal weight, blocking that population from reaching 100% overweight and obesity. While it is possible that under some conditions, there may be a rise in proportion of individuals who are classified as overweight in these lower BMI groups, it is much more likely that the realistic maximum combined rate of obesity and overweight is less than 100%.

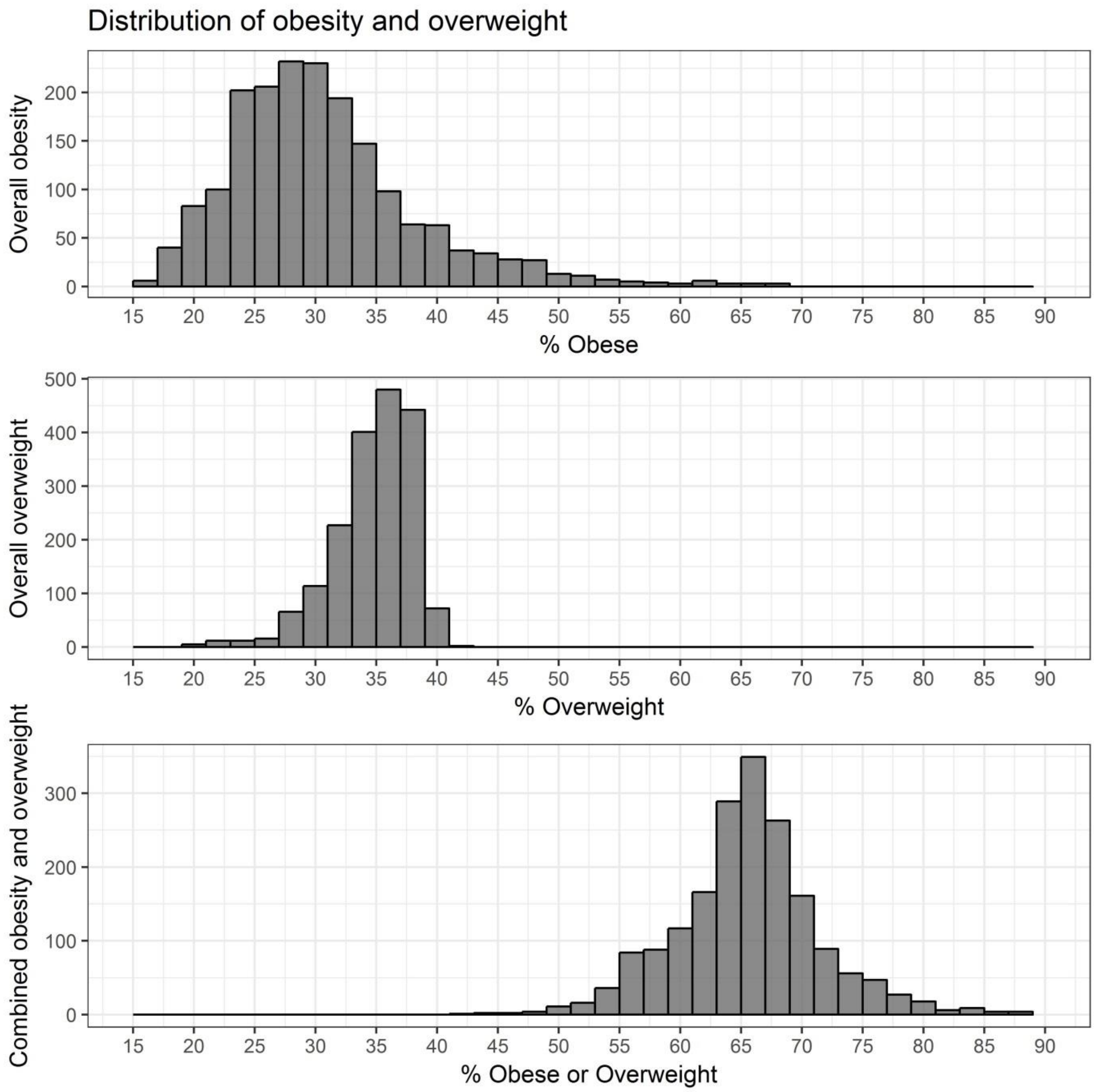


Figure 5.1: Distribution of obesity (BMI), overweight and combined estimates

5.2.2 Maps of obesity prevalence

As described above (Sub-section 5.2.1), estimated obesity rates for CAUs varied from 15.3% to 67.2%. Both of these extremes are located in Counties Manukau DHB, roughly 25 minutes' drive apart[27] (the lowest estimate, 15.3%, in the East Tamaki area, the highest, 67.2%, in Mangere). Of the 51 CAUs with obesity rates over 50%, more than half (28) are in Counties Manukau, all are in the North Island. The remainder are in Northland (2), Auckland

[27] According to typical travel time estimates from Google Maps.

(1), Waikato (2), Bay of Plenty (5), Tairawhiti (4), Lakes (3), Hawke’s Bay (1), Wanganui (1), Capital and Coast (4).

The obesity (BMI) map in Figure 5.2 shows a marked similarity to the deprivation (see Figure A.1), and the map of obesity based on waist measurement (Figure 5.3) is also very similar. The two are not identical, however, as large sections of eastern Christchurch are classified as ‘most deprived’, and though obesity is high in this area it is split across quintiles 4 and 5 (highest and second highest), rather than uniformly occupying the highest obesity quintile. Conversely, South Auckland is dominated by the highest quintile of obesity, but contains several pockets of slightly lower deprivation. Central Auckland on the other hand has high deprivation and low obesity rates demonstrating that though deprivation is an important determinant of obesity — as discussed in Sub-sections 2.2.2 and 2.3.4 and demonstrated by McLaren (2007); Moore and Cunningham (2012); Sobal and Stunkard (1989) — it is not a sufficient measure alone. These differences are likely due to variations in ethnic and age composition, south Auckland has large Māori and Pacific populations whereas Christchurch has very low numbers of these groups. Central Auckland has large populations of young people (students) and those of Asian ethnicity; both of these groups exhibit low obesity rates, and students tend to have low incomes. Comparisons between obesity and deprivation will be more thoroughly explored in Sub-section 5.2.3.

The same overall pattern can be observed when the data are restricted to only those most severely obese (BMI $\geq$ 40), see Figure 5.4. Concentrations of areas with high levels of severe obesity are broadly found in the same areas, however these individuals are spread slightly more evenly across areas with less obvious distinction between areas with high and low rates compared to the WHO obesity threshold of BMI $\geq$ 30 shown in Figure 5.2. This is evident in the encroachment of higher quintiles into the central Auckland area relative to the quintile category assigned in the BMI $\geq$ 30 obesity map.

The combined obesity and overweight estimates (Figure 5.5) are very similar to the obesity only map with only slight changes in the pattern. Areas of central Auckland which exhibited obesity rates in the mid-range (quintiles 2-4), have generally shifted to a lower quintile of combined obesity and overweight. Other areas, such as the rural South Island have shifted to higher quintiles when obesity and overweight are combined. Estimated rates of combined obesity and overweight ranged from 41.2% in Palmerston North (Mid Central DHB — associated with a University) to 87.8% in Counties Manukau (this time in Otara). Extremely high values were not concentrated in Counties Manukau to such a degree when obesity and overweight were combined. Of the 115 CAUs with combined obesity and overweight of 75% or more, 35 were in Counties Manukau (30.4% of areas with combined obesity and overweight above the 75% threshold). The remaining areas were found in Hawke's Bay (14), Waikato (13), Northland (11), Lakes (10), Bay of Plenty (10), Tairawhiti (9), Auckland (6), Capital and Coast (5), Wanganui (1), and Hutt Valley (1). Maps for overweight alone can be found in Figure D.1[28].

Diabetes prevalence echoes obesity prevalence in many respects, with the highest rates generally found in the most deprived and highest obesity areas (Figure 5.6). However, the rates of diabetes are much lower (the highest estimate is 15.7%, in Porirua, part of Capital and Coast DHB) and there is less distinction between areas. Diabetes estimates also reflect differences in the age profile of populations as type II diabetes is much more common in older people, so there are slightly elevated diabetes rates in eastern central Auckland around Remuera and Kohimarama, and also western Christchurch, but diabetes rates remain very low in Auckland City. The NZHS microdata sample did not distinguish between type I and type II diabetes, so the model is also unable to make this distinction. Type I diabetics may reasonably be considered to be randomly distributed throughout the population, so this is not of great concern.

[28] Note that the overweight only maps show an inverse relationship to the obesity and combined obesity and overweight maps due to the obesity and overweight categories being mutually exclusive, as discussed previously (Section 5.2.1).

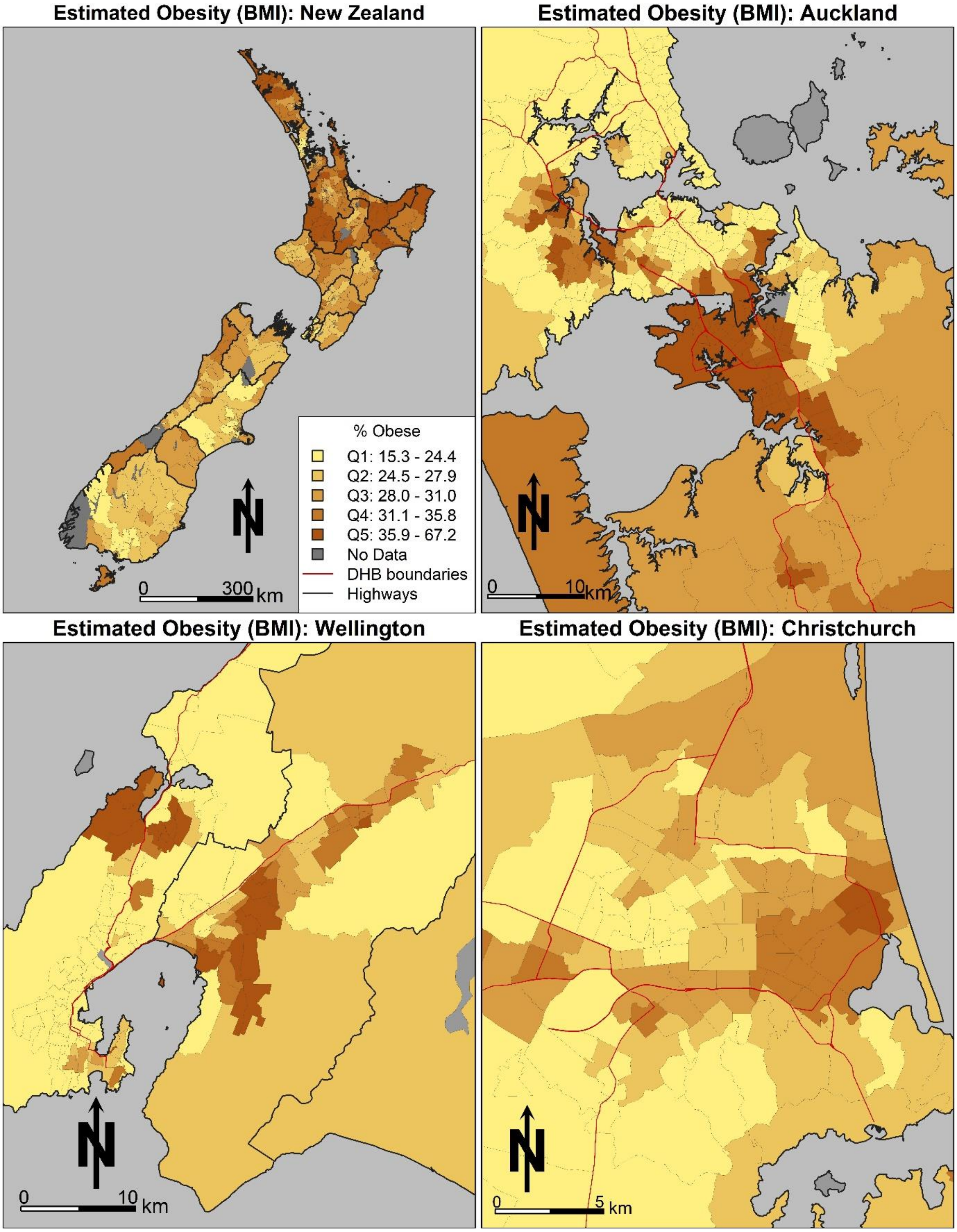


Figure 5.2: Estimated obesity prevalence in Aotearoa New Zealand and the three largest cities

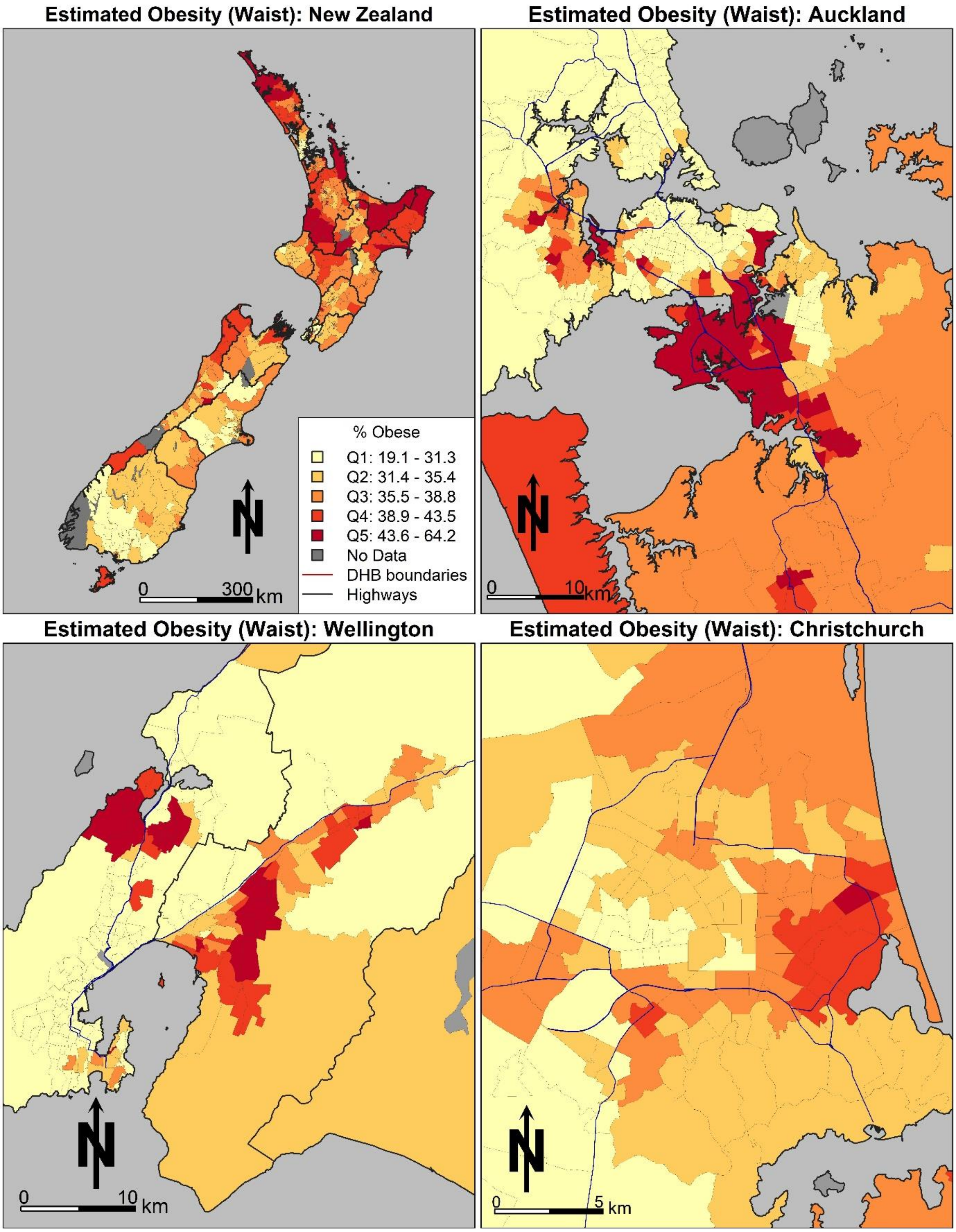


Figure 5.3: Estimated obesity prevalence using waist measurements in Aotearoa New Zealand and the three largest cities.

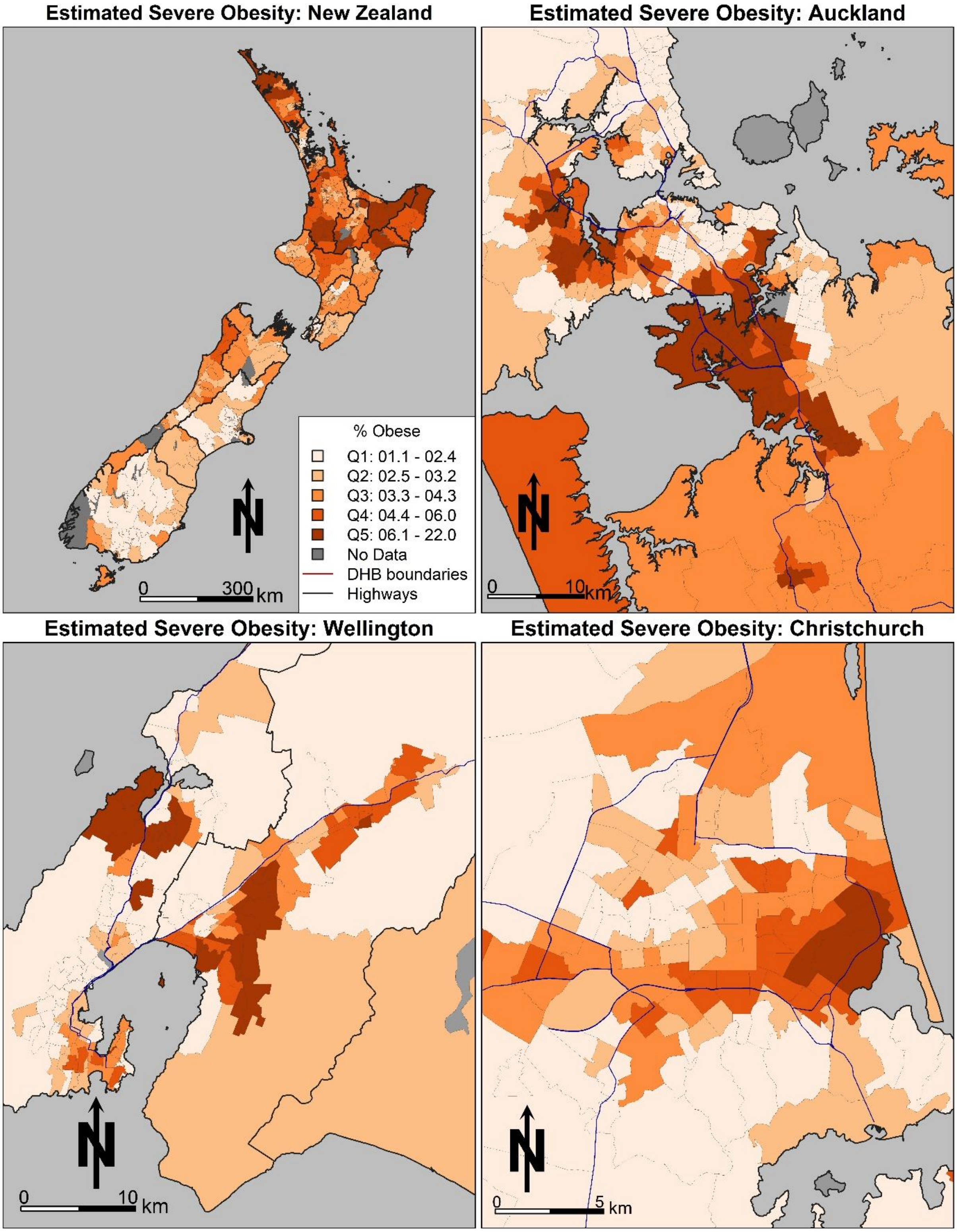


Figure 5.4: Estimated severe obesity prevalence (BMI ≥ 40) in Aotearoa New Zealand and the three largest cities

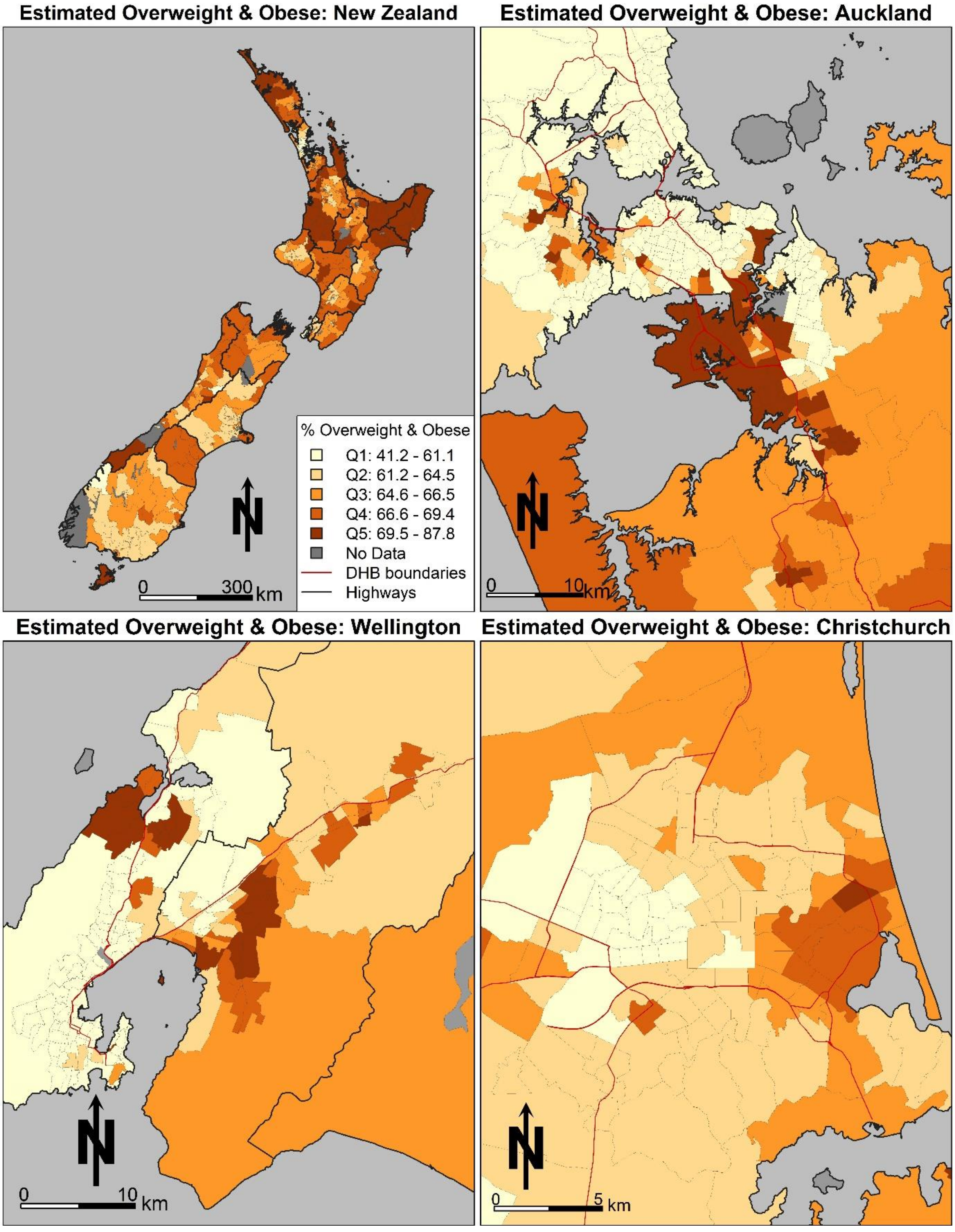


Figure 5.5: Estimated combined overweight and obesity prevalence (BMI ≥ 25) in Aotearoa New Zealand and the three largest cities

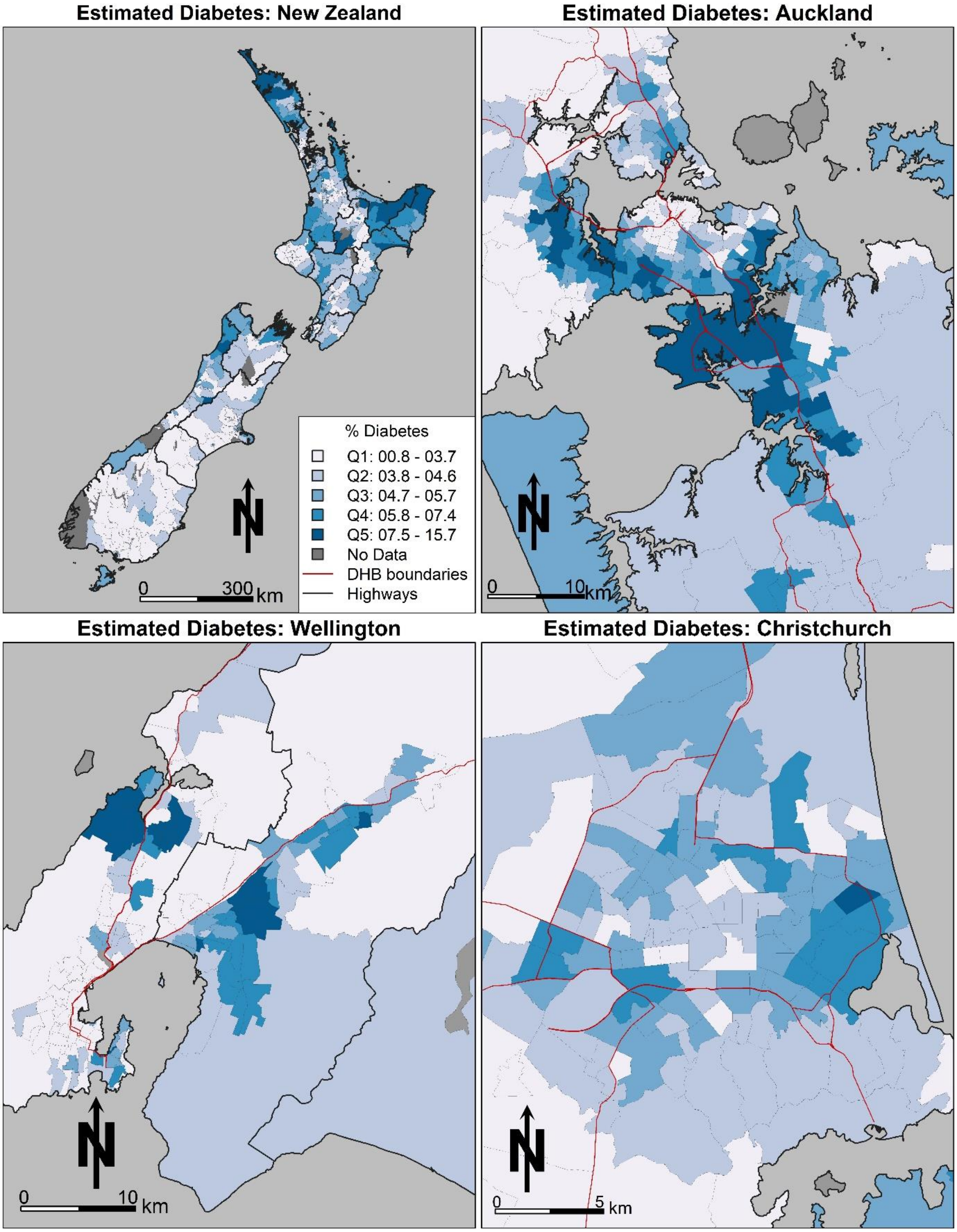


Figure 5.6: Estimated diabetes prevalence in Aotearoa New Zealand and the three largest cities

5.2.3 Analysis of obesity estimates

In this section, the obesity rates generated by SimAotearoa will be further analysed and examined using overlays and an analysis of significant clusters of high and low obesity rates. First the overlap between obesity and deprivation will be assessed to identify the extent to which these two variables overlap; this will help to tease out relationships between the two, identifying places where obesity rates are higher or lower than might be expected based on deprivation. Also examined are the overlap between obesity and severe obesity as well as the overlap between obesity and diabetes. Finally, cluster analysis (local *Moran's I*) will be used to identify statistically significant clusters of obesity and relationships with neighbouring areas.

If deprivation is to be used as a proxy for obesity, then areas of high deprivation should also generally be areas of high obesity. It is therefore worth comparing where high levels of deprivation and obesity occur simultaneously. To produce the overlaid map of obesity and deprivation, areas which fell within both the highest obesity quintile and the highest deprivation quintile were identified (371 CAUs in each). Then, these areas were compared to identify which areas were in the highest categories of both obesity and deprivation. In total, 293 CAUs (79.0% of high obesity areas) were identified as having both high obesity and high deprivation, only 78 CAUs per variable were associated with high levels of only one of these variables. Additionally, 1400 CAUs were not within the highest category for either variable.

The strong overlap between obesity and deprivation suggests that deprivation is often a good proxy for obesity, but care should be used in areas that are not congruent between these two variables. Deprivation as a proxy for obesity should also be interpreted within the context of the population variables that have been previously discussed (particularly age and ethnicity). Figure 5.7 shows that areas of lower deprivation but high obesity rates are found in South Auckland, Wellington, Waikato and some other rural areas (Figure 5.7). Areas with high deprivation and lower obesity rates were mostly found in western and central Auckland as well as Christchurch. Similar results were obtained using the two highest categories, instead of only the highest category; these can be found in Figure D.3.

It is also worth considering whether the severity of obesity is uniform, or whether some areas may have lower levels of obesity, but higher levels of severe obesity. To do this, the highest obesity category (371 CAUs) was compared with the highest category of severe obesity (381 CAUs) as above. Areas with the highest category of both obesity (BMI ≥ 30) and severe obesity (BMI $\geq$ 40) were identified (348 congruent CAUs, 93.8% of high obesity areas), along with those that were in the highest category only for severe obesity (more severe, 33 CAUs) or obesity (less severe, 23 CAUs), and finally those areas not in the highest category for either variable (1445 CAUs), see Figure 5.8. Most areas with lower categories of severe obesity compared with obesity were in rural areas of Waikato DHB. Relatively higher rates of severe obesity were found in areas peripheral to congruent high obesity areas in west Auckland, Porirua, Lower Hutt, and Christchurch. Similar results were also found for diabetes, with 287 CAUs (77.8% of high obesity areas) classified in the both highest obesity and the highest diabetes category (of 371 CAUs in each). A further 84 areas were classified in highest category for one of these variables, with 1394 CAUs were classified in one of the lower categories, see Figure 5.9.

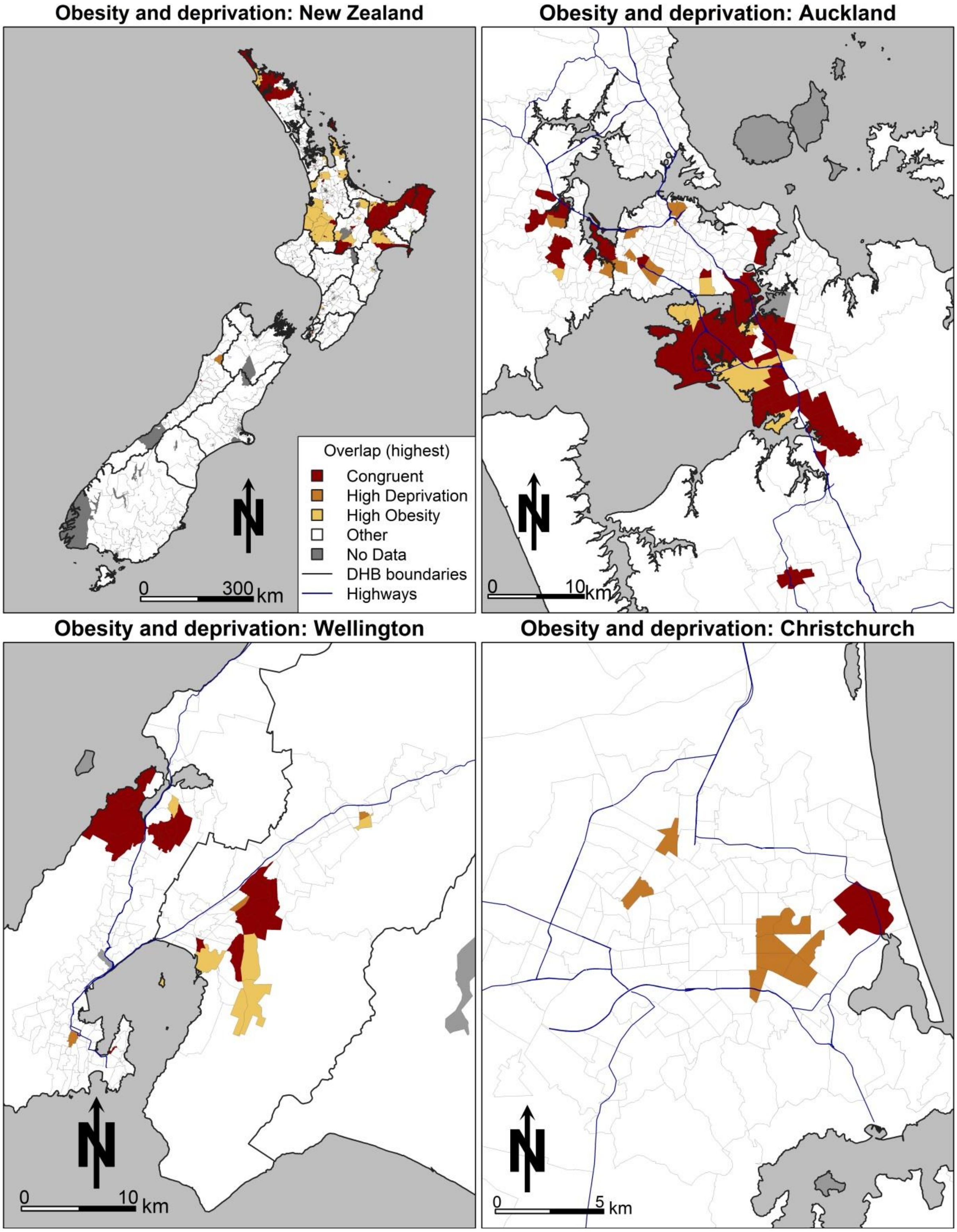


Figure 5.7: Overlay of the highest categories of obesity and deprivation. Congruent areas have both the highest obesity rates and the highest deprivation category.

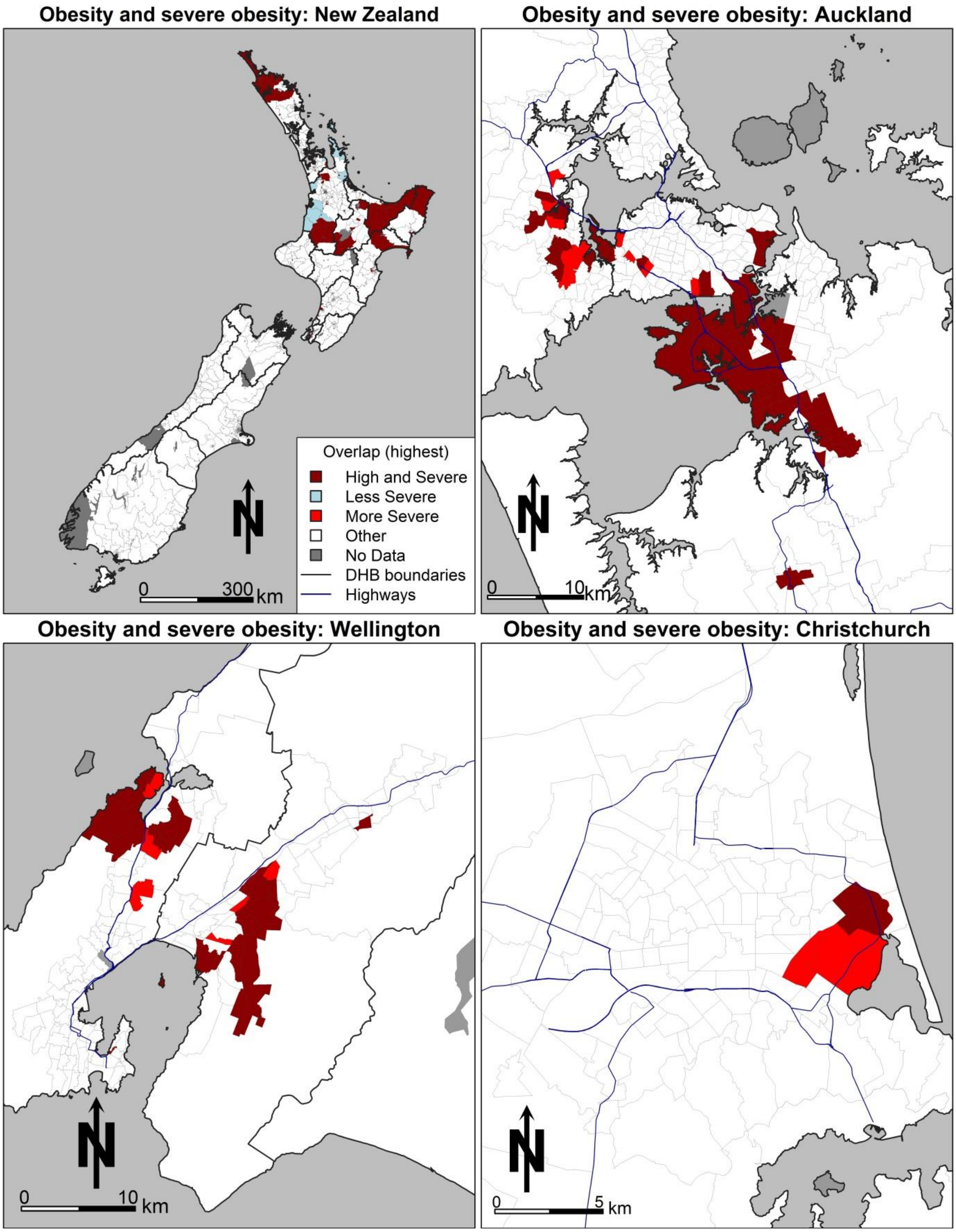


Figure 5.8: Overlay of the highest categories of obesity (BMI ≥ 30) and severe obesity (BMI ≥ 40).

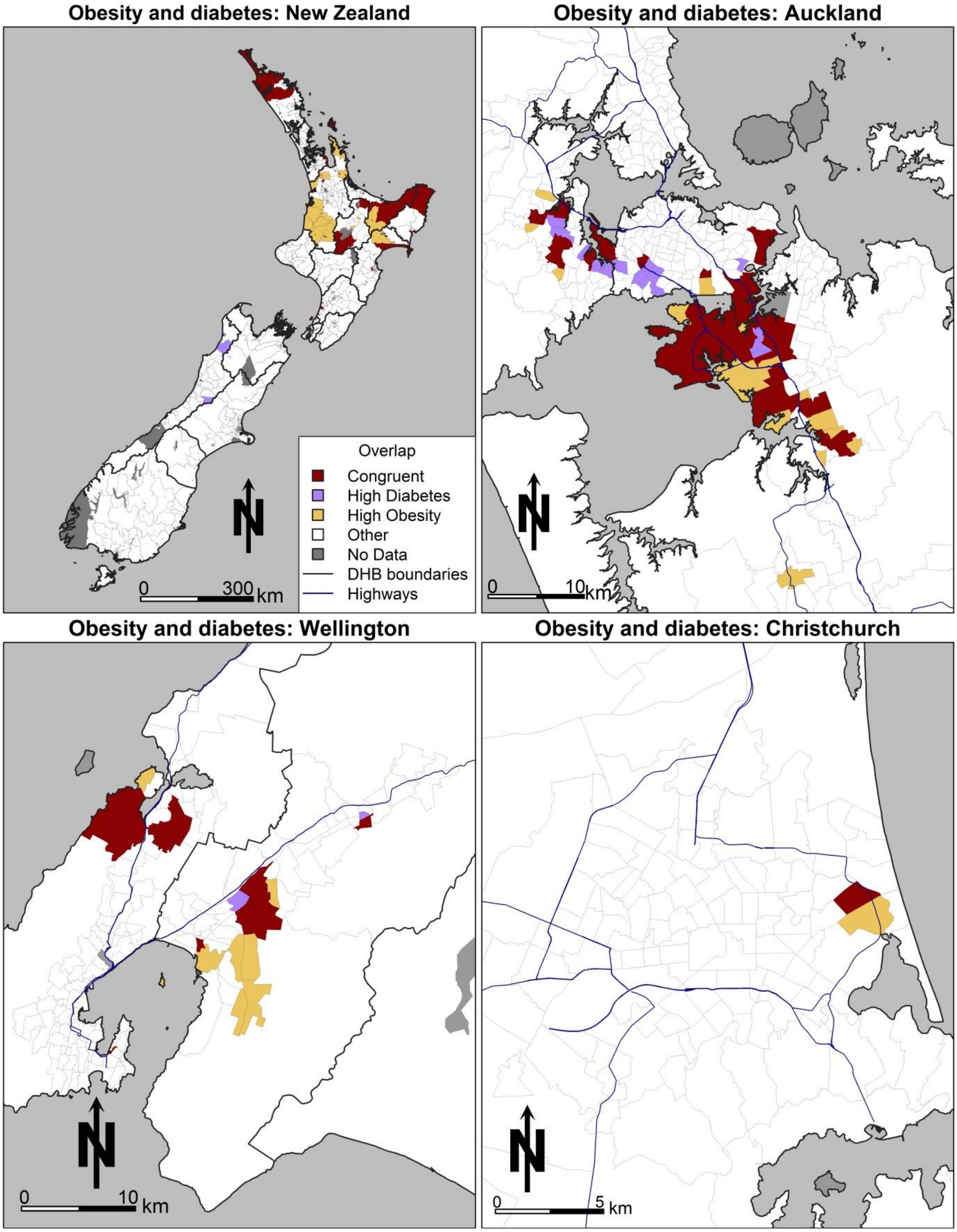


Figure 5.9: Overlay of the highest obesity (BMI ≥ 30) and diabetes categories. Congruent areas have the rates in the highest category for both variables.

The correlation between estimated obesity and diabetes rates can be seen in Figure 5.10. This Figure also shows that both of these variables are strongly sorted by deprivation index. The split is not exact — there is quite a lot of overlap — but there are clearly bands in which areas of a particular deprivation level are most likely to be found.

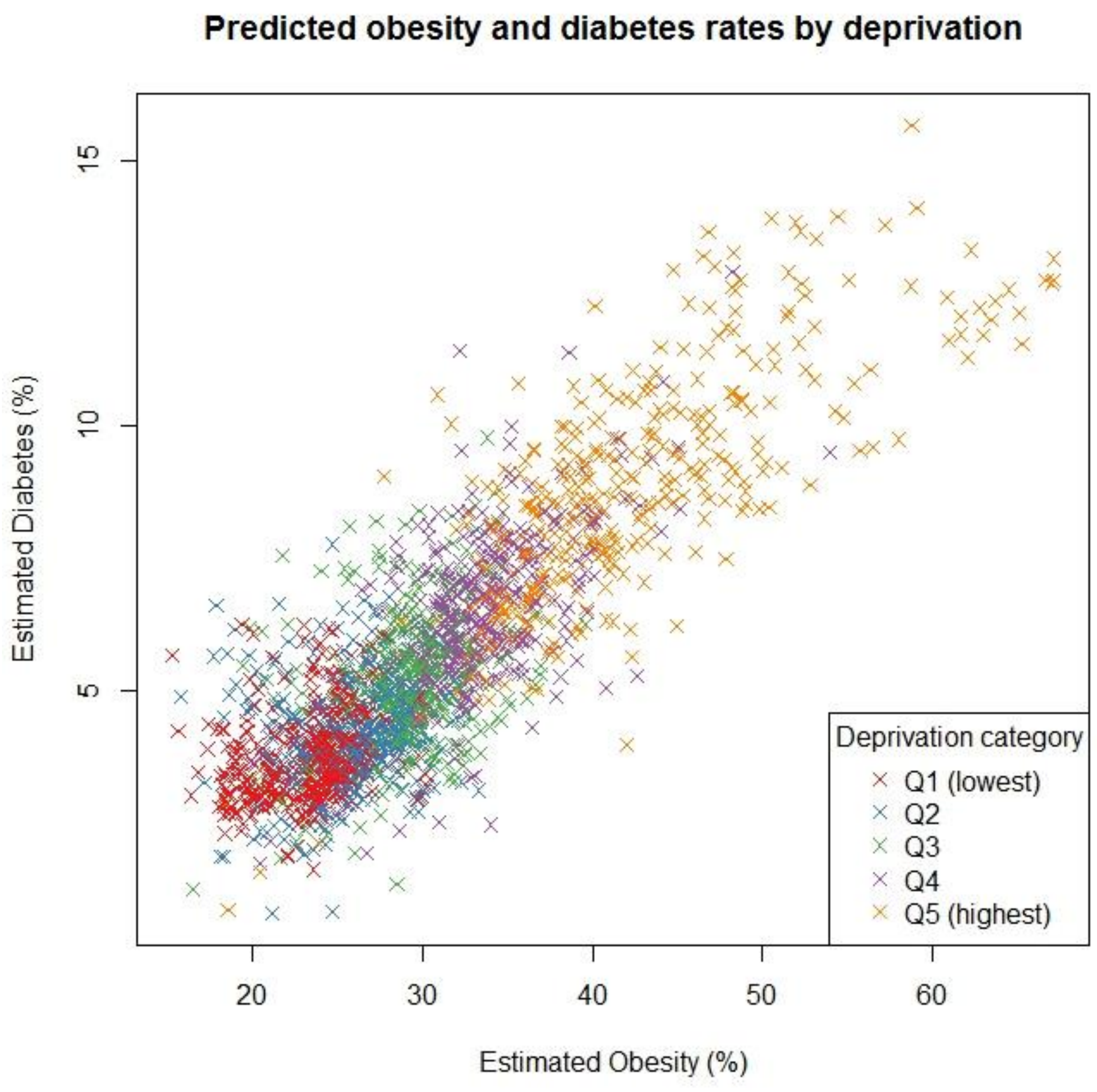


Figure 5.10: Estimated obesity rates plotted against estimated diabetes rates and coloured by deprivation index value.

Assessing the statistical significance of the apparent clusters of high obesity areas is also a valuable tool. The method selected for this is called the local Moran's I (Anselin, 1995; ESRI, 2017). This method calculates statistically significant hotspots and identifies each area as a member of a cluster (high areas or low areas), as an outlier (a high area adjacent to a low area, or vice versa), or as not significant. The cluster analysis was performed using the software ArcMap (ESRI, 2013). The integrated tool *Anselin Local Moran’s I* (ESRI, 2017) was used with spatial relationships conceptualised using contiguous areas[29] (edges and corners). For these data, 165 CAUs were identified within high obesity clusters, 196 CAUs were identified within low obesity clusters, and only one outlier was found: a low obesity area next to a high obesity cluster in Porirua (Figure 5.11), the remaining 1487 CAUs were not statistically significant. The most substantial clusters of high obesity were found in Northland, Gisborne, Waikato, South Auckland, Porirua, and Lower Hutt. Low obesity clusters are mostly found in cities: Northern and Central Auckland, Wellington and Kapiti Coast, Western and Southern Christchurch.

[29] Using the fixed distance and optimised analysis options produced issues resulting from the land geometry and edge effects, particularly in Auckland as it is a narrow isthmus bounded by two harbours. Neither of these alternatives produced reasonable results when compared with the prevalence map; thus contiguous edges and corners were used in this analysis.

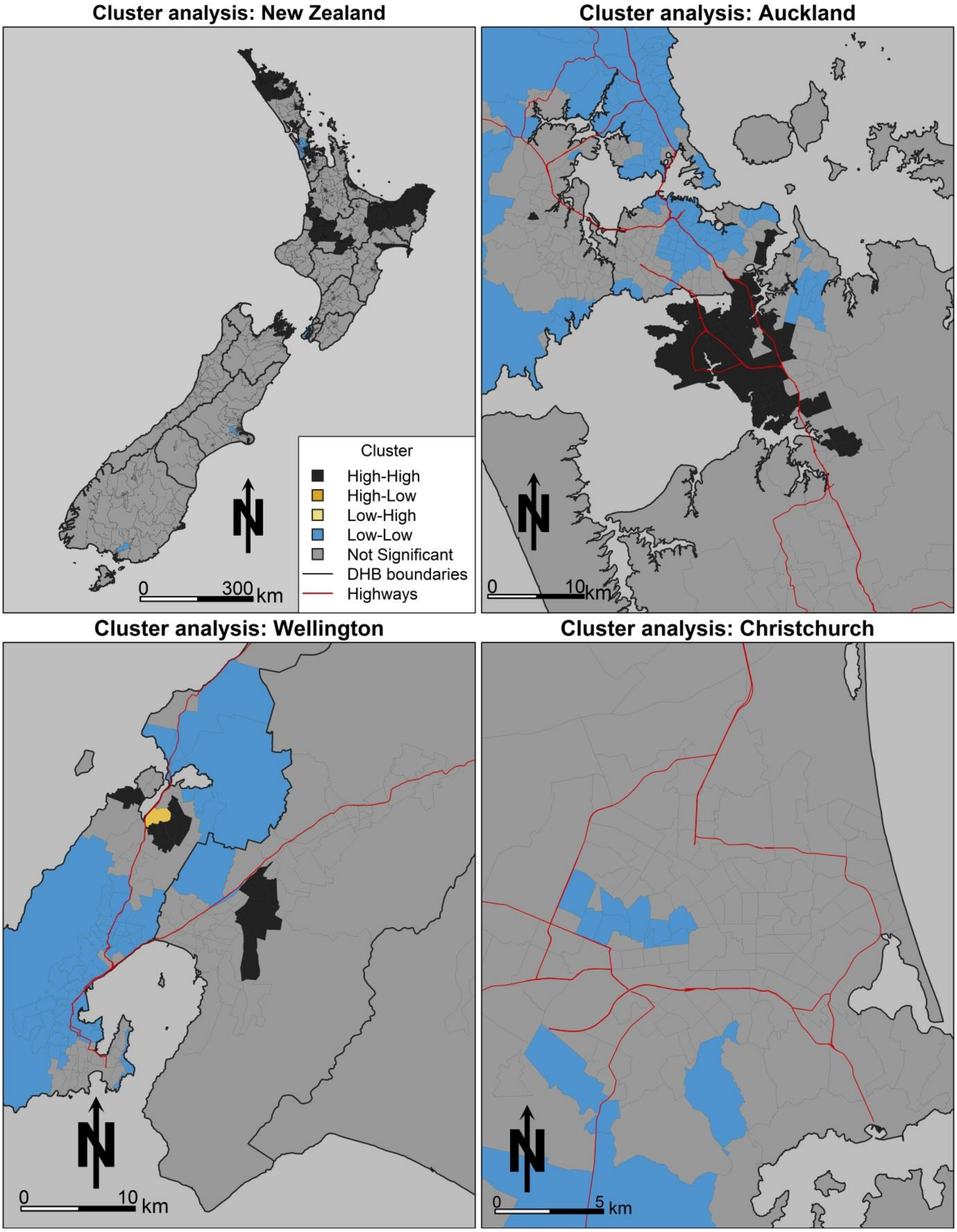


Figure 5.11: Local Moran's I analysis, showing areas with significant clusters of high or low obesity areas.

5.2.4 Subpopulation results

One of the strengths of SMSM is that it is a relatively simple exercise, once the simulated population has been generated, to extract information about a population subgroup of interest. This section will display results for several subpopulations: each of the four main ethnicities, young adults (age 15-24), and each sex. Māori and Pacific Peoples have high obesity rates and are a key target population for reducing health inequities (Ministry of Health, 2015a), as discussed earlier (Section 3.4). Young adults are a key target population for obesity interventions to reduce obesity rates over the long term. Maps in this section will calculate obesity in the target group relative to the size of the group, excluding areas with a low number of targeted individuals.

The pattern of obesity in Māori is very similar to that in the overall population; though all estimated obesity rates shift significantly higher for Māori[30] (Figure 5.12). However, a few small differences can be observed in Counties Manukau. The overall obesity map (Figure 5.2) shows a small patch of lower obesity rates around Papatoetoe (between the two highways in southern Auckland), this is not evident on the map of Māori obesity, the whole area has been categorised in the highest quintile of obesity. In addition, relatively higher rates of obesity are observed for Māori in parts of East Tamaki and Howick. This suggests that patterns of obesity among Māori match the overall patterns of obesity, but with higher rates of obesity, however Māori in some parts of southern Auckland are predicted to have disproportionately higher rates of obesity than observed in the overall pattern.

The maps for obesity in Pacific Peoples are harder to interpret due to low populations in many parts of the country, with visible CAUs in all displayed maps largely restricted to urban areas (Figure 5.13). Pacific obesity in Wellington generally matches the patterning of the overall obesity map (Figure 5.2), but there are differences for Auckland and Christchurch. In Auckland, though the highest rates are still observed in southern and western Auckland, there is substantial encroachment of higher categories of obesity into the central Auckland area. In Christchurch, the highest obesity rates have been shifted towards the central city and in some

[30] For this reason, it is not possible to use the same quintile scale from the map of overall obesity on the map of Māori obesity as the map would become unreadable. Quintiles 2 and above on Figure 5.12 would fall into the highest quintile on the overall map scale. Similar problems can be observed for Pacific (also too high) and Young people (too low)

respects more closely resembles the distribution of the Pacific population (see Figure A.8) than the overall obesity map.

European and Asian populations are of less concern than Māori or Pacific Peoples, but it is worth investigating these for comparative purposes. In the Asian population, there was much less differentiation between areas (Figure 5.14). Levels of obesity still showed broadly the same pattern, but the different categories mixed together to a greater extent with little evidence for pockets of high obesity. Europeans make up the majority of the population of Aotearoa New Zealand, so results (Figure 5.15) are expected to be very similar to the whole population. The notable exception to this similarity of patterning is in Howick, which shows much higher obesity rates, this is likely due to the exclusion of the large local Asian population from this set of estimates.

Again, the pattern for young adults is very similar to the overall pattern of obesity, though this time the estimated rates of obesity are lower (Figure 5.16). Relatively speaking, rates were somewhat lower in rural areas (particularly South Canterbury, but also in southern Waikato). Conversely, in urban areas, rates drifted into higher obesity categories in places where adults overall remained in lower categories. This is particularly evident in central Wellington, central and western Christchurch, and Central Auckland.

The maps for both men (Figure 5.17) and women (Figure 5.18) are very similar to the overall obesity map in Figure 5.2; however, small differences can be detected. For men, obesity rates are slightly lower than the overall rate in deprived urban areas such as eastern Christchurch, the Hutt Valley, and Western Auckland (more areas had estimates within a lower obesity quintile). Women show slightly higher obesity rates in the deprived urban area in eastern Christchurch (a larger number of areas had estimates in the highest obesity quintile), and generally slightly lower obesity in rural areas, particularly in the South. The quintile colour categories for these figures are fixed to the same values as the overall obesity maps (Figure 5.2) to facilitate this comparability, varying only minimum and maximum values.

Women generally exhibit higher levels of obesity than men, so the relatively higher rates for women observed in deprived areas can be understood in this context. It is less clear why lower rates were observed for women in rural areas. This could be an artefact of the SMSM procedure, but many of these areas tend to have relatively low rates of deprivation and are predominantly New Zealand European, and so would be expected to also have low rates of obesity. The same patterning may not be observed in men for the same areas due to carrying higher than normal muscle mass from doing highly physical jobs such as farming, or it may be a result of the age profile for these areas (though it would be expected for women to exhibit a similar pattern if age was the cause). The majority of these were fitted with the full (three year) model, using microdata from the whole of Aotearoa New Zealand, but this pattern is also observed in South Canterbury, which was fitted using the rural model, so it is unlikely to be caused by model selection.

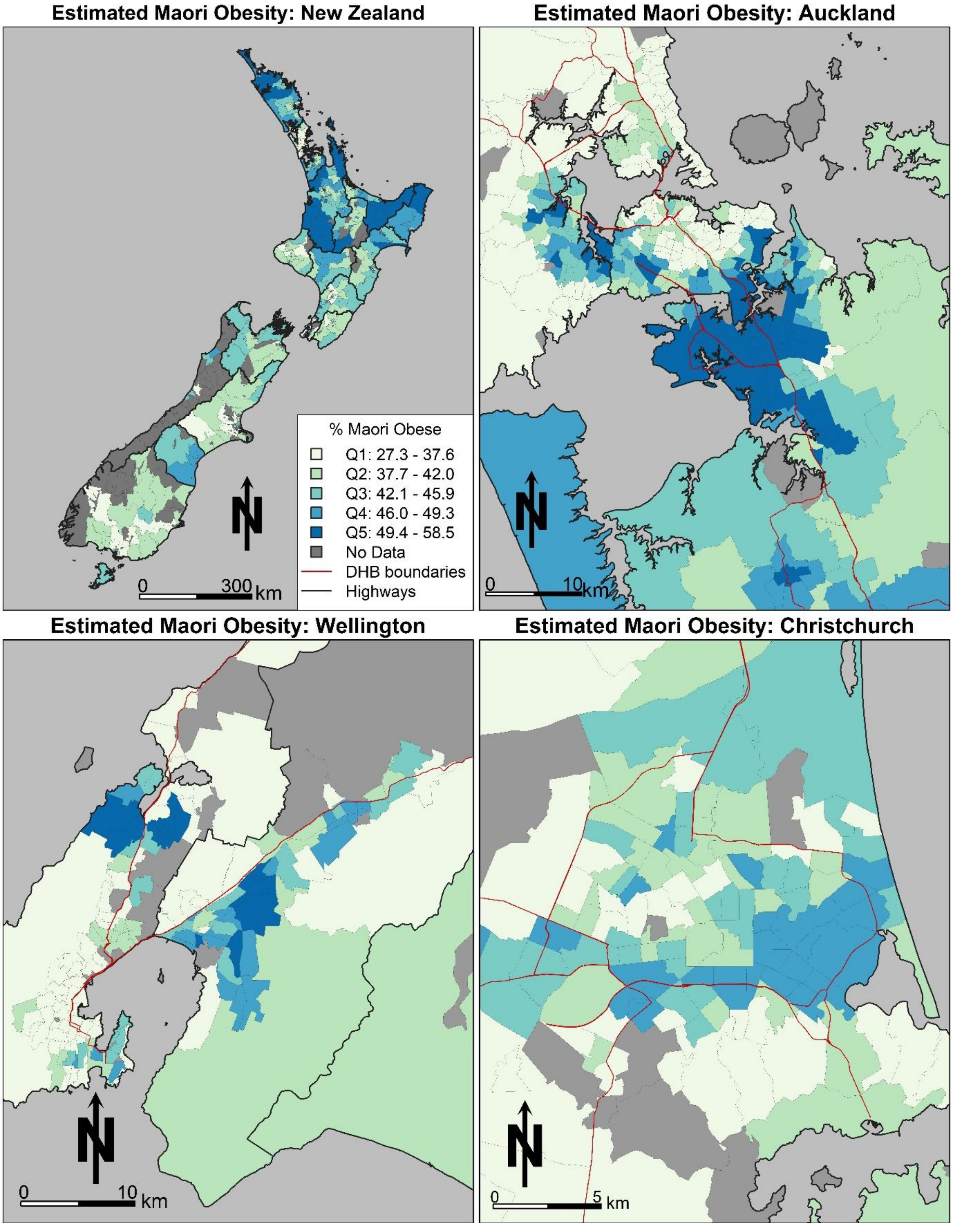


Figure 5.12: Percentage of Māori who are obese, excluding areas with fewer than 30 Māori individuals.

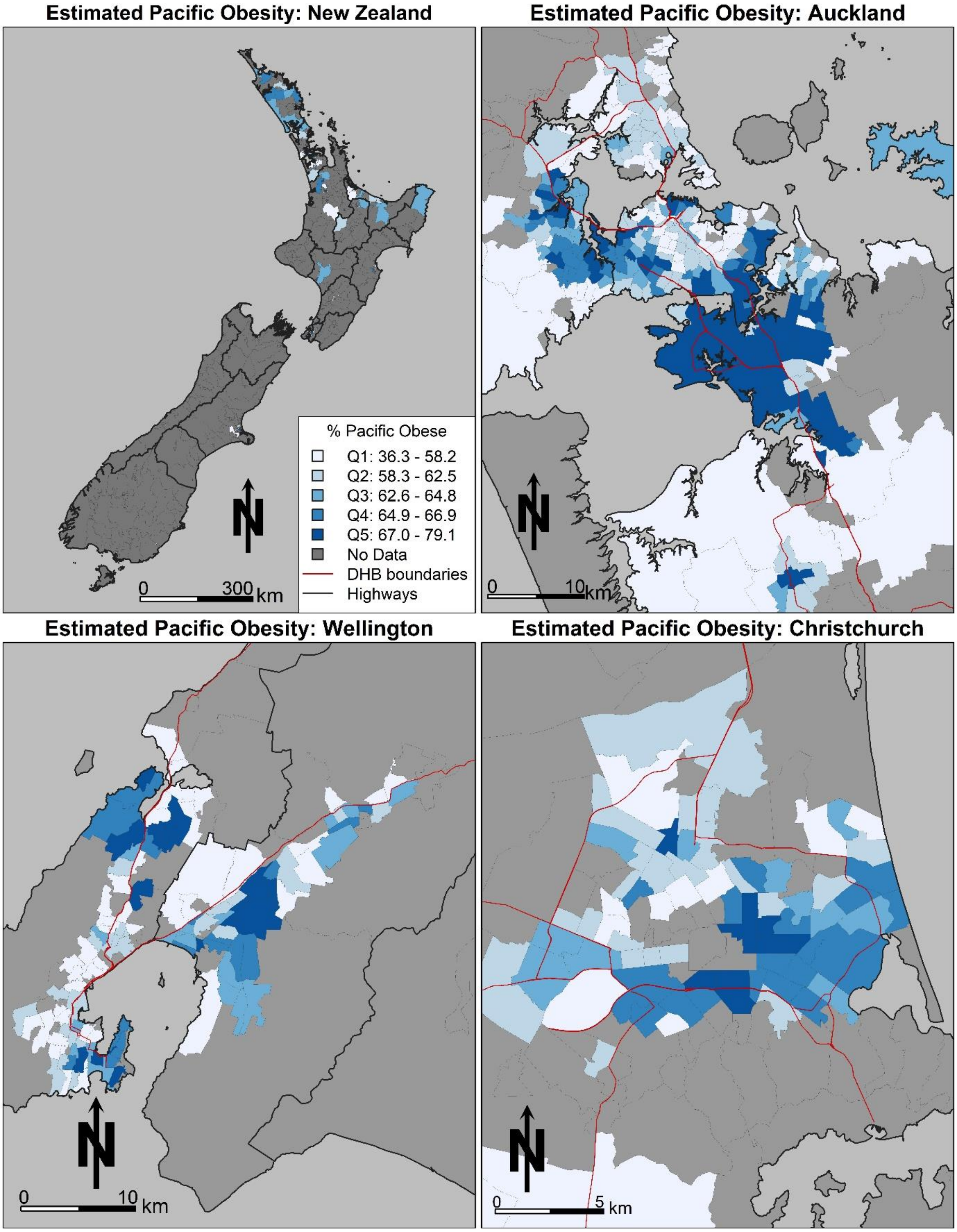


Figure 5.13: Percentage of Pacific Peoples who are obese, excluding areas with fewer than 30 Pacific individuals.

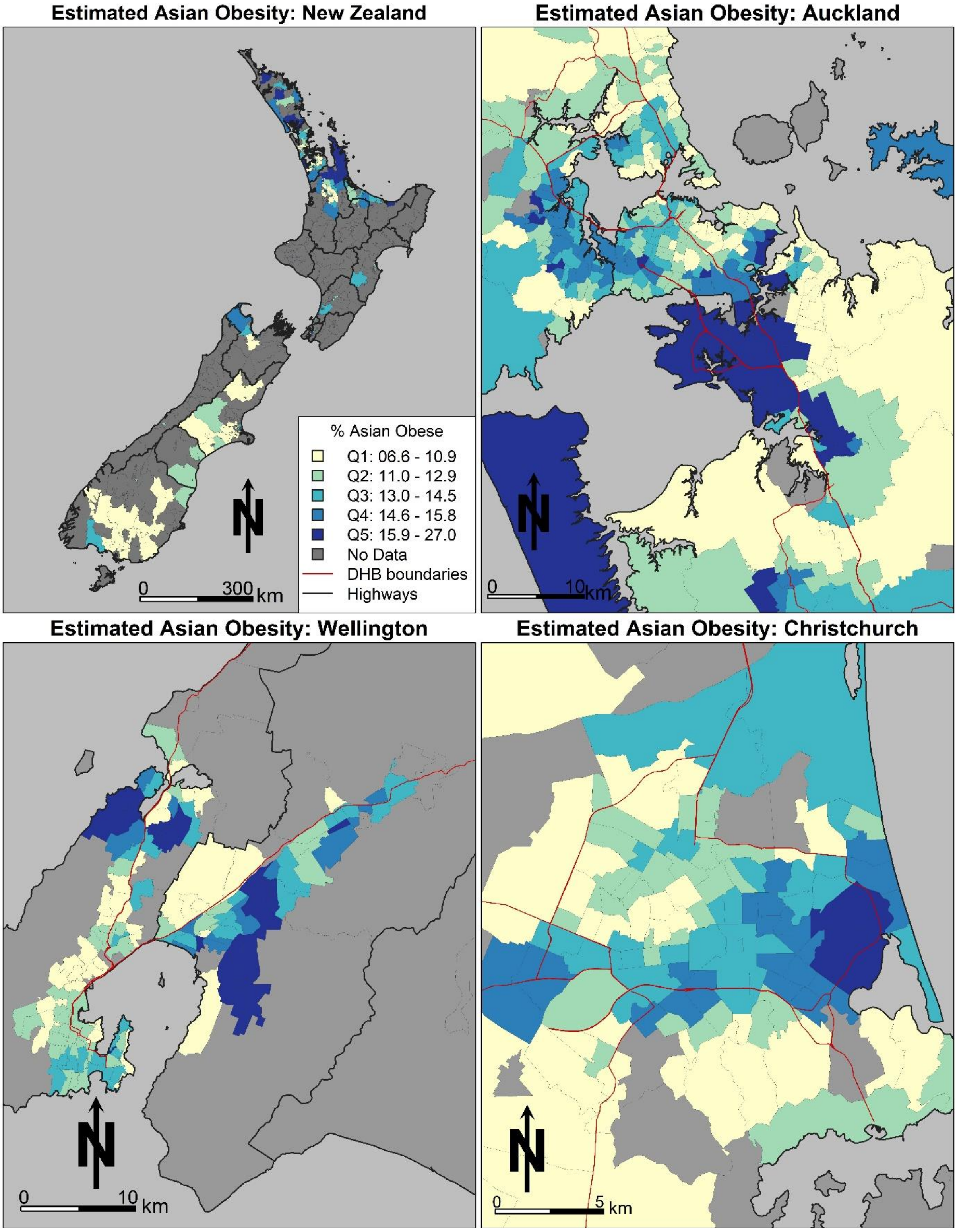


Figure 5.14: Percentage of people in Asian ethnic groups who are obese, excluding areas with fewer than 30 Asian individuals.

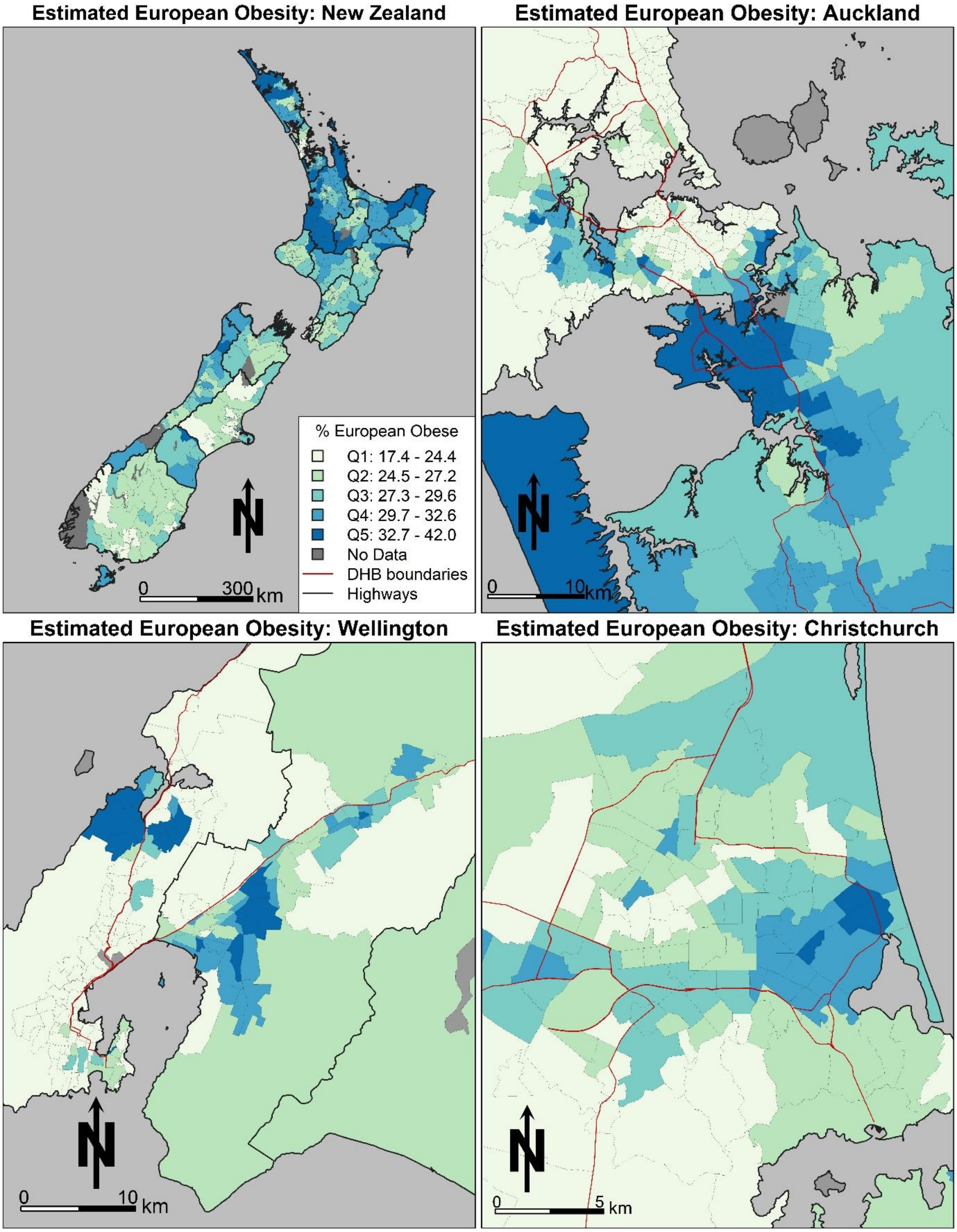


Figure 5.15: Percentage of Europeans who are obese, excluding areas with fewer than 30 European individuals.

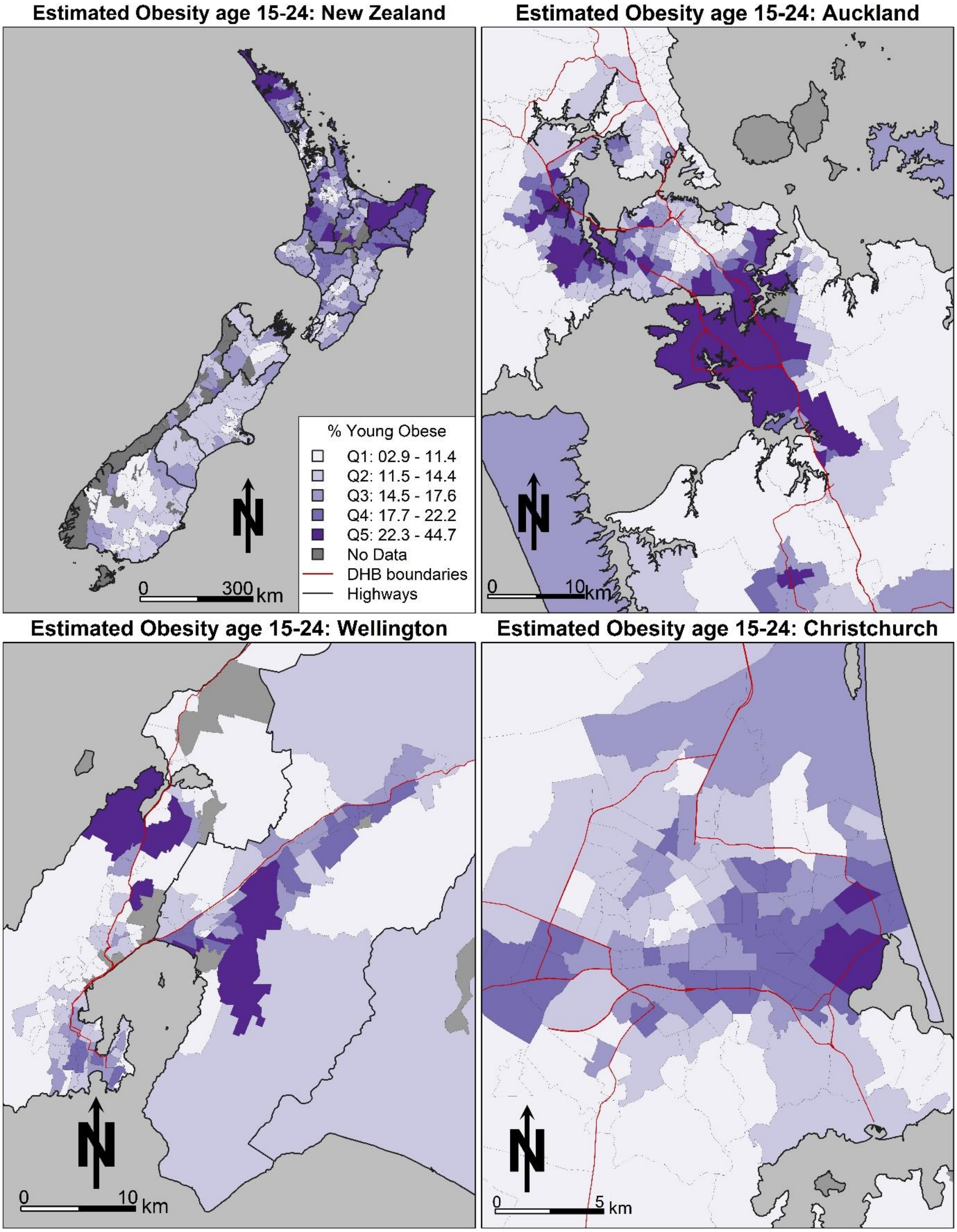


Figure 5.16: Percentage of Young people (age 15-24) who are obese, excluding areas with fewer than 30 young individuals.

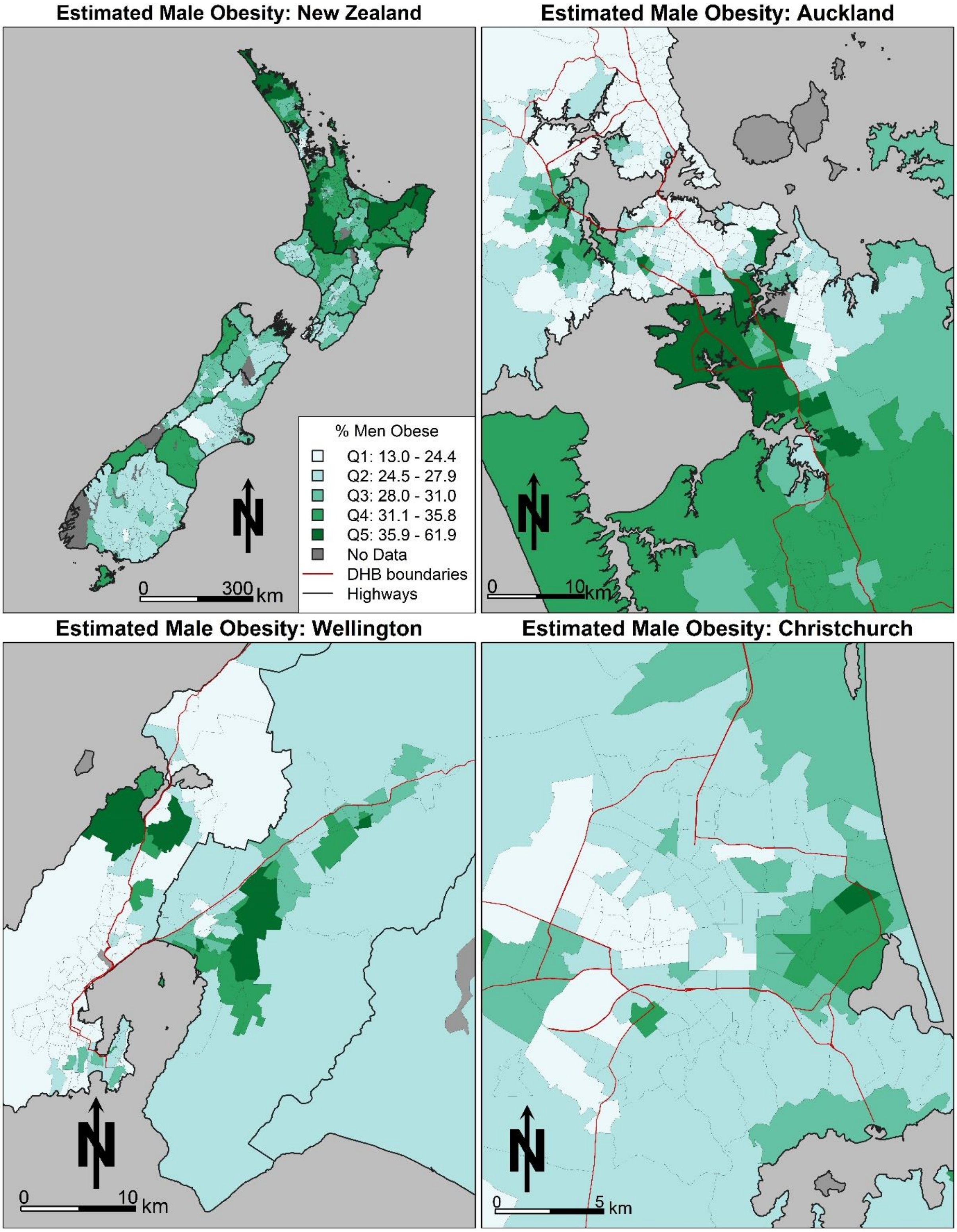


Figure 5.17: Percentage of men who are obese, excluding areas with fewer than 30 men.

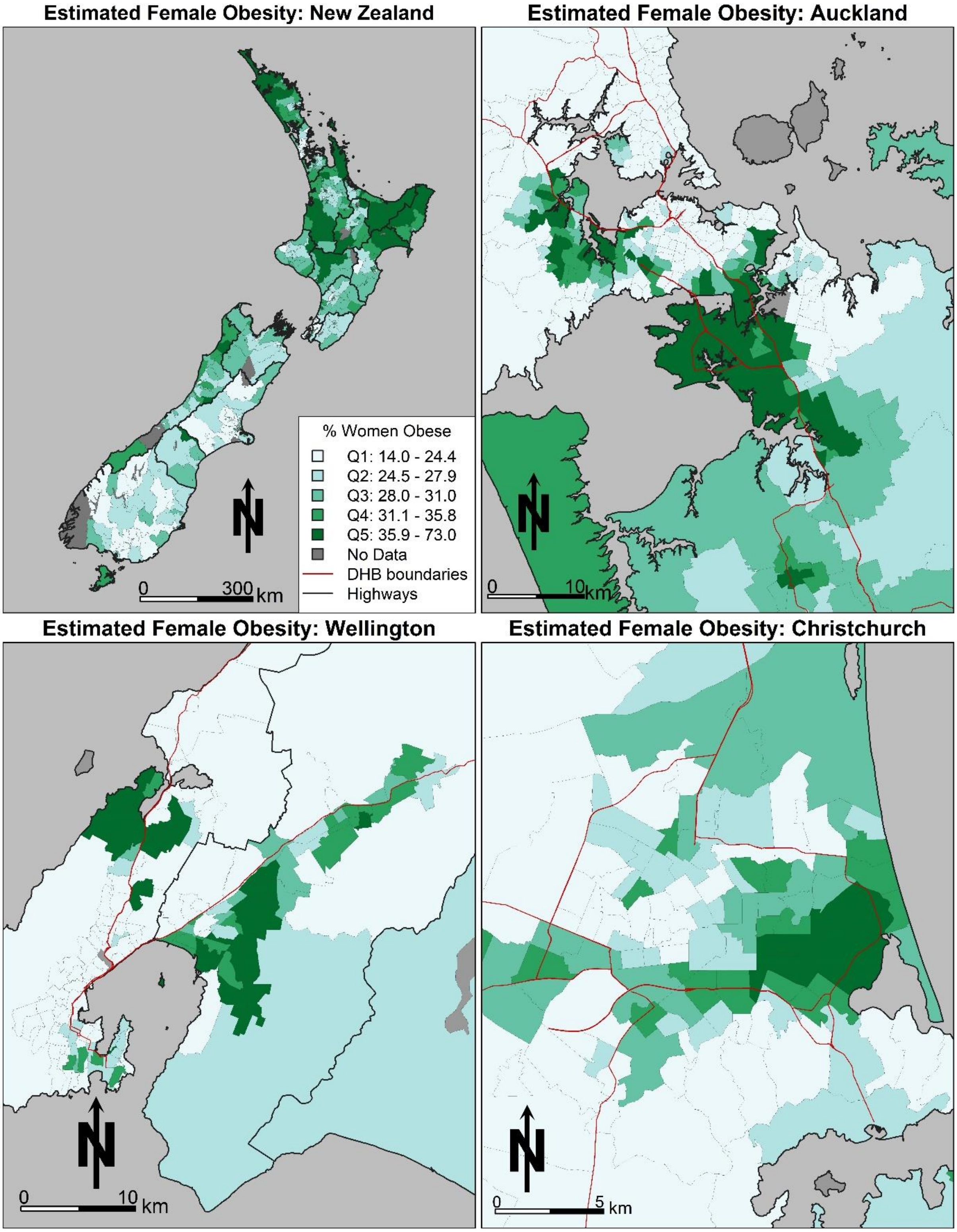


Figure 5.18: Percentage of women who are obese, excluding areas with fewer than 30 women.

When the subpopulation results are aggregated by DHB (Table 5.3), patterns similar to those for the overall population (Table 5.1) are evident, particularly for Māori, Europeans, and young people. Obesity rates are lower than the national rate in Auckland, Waitemata, Capital and Coast, and Canterbury, but higher in Counties Manukau, Tairawhiti, Waikato, and Northland. Pacific Peoples, however, exhibit a different pattern: an elevated rate of obesity in Counties Manukau DHB only, with slightly lower obesity rates everywhere else. This result is likely due to the very strong concentration of Pacific Peoples within Counties Manukau DHB (20% of this DHB is of Pacific ethnicity, much higher than any other DHB according to Census data). Other possible explanations include an increase in ethnically mixed individuals outside of Counties Manukau, differences in relative deprivation of Pacific populations in different DHBs or different behavioural patterns depending on the composition of the area. There appears to be little difference in the spread of obesity rates among Pacific Peoples in different DHBs, rates vary but remain high in all DHBs, with little differentiation between them (a selection of DHBs can be seen in Figure 5.19). Conversely, obesity rates among Māori follow the pattern of overall obesity rates, though the rates themselves are higher than the general population and lower than among Pacific Peoples. A version that includes all DHBs is available in Figure D.6.

Table 5.3: Subpopulation results aggregated by DHB

% Obesity	NZHS overall	Māori	Pacific	Asian	European	Young (15-24)
National	29.7	46.6	66.3	13.8	27.7	18.1
Auckland	21.8	43.4	65.1	13.0	23.9	16.5
Bay of Plenty	31.7	48.2	63.5	14.3	29.5	19.1
Canterbury	27.7	42.2	62.6	12.6	26.5	15.2
Capital and Coast	25.5	40.7	64.5	12.0	23.2	16.2
Counties Manukau	37.7	51.0	70.0	16.0	31.2	24.5
Hawke's Bay	33.8	48.2	65.2	14.3	29.5	20.1
Hutt Valley	31.0	45.7	64.7	13.9	28.2	19.6
Lakes	34.0	48.2	63.5	14.8	30.2	21.5
Mid Central	31.4	45.5	62.5	13.7	29.3	18.2
Nelson Marlborough	27.5	44.1	62.7	14.0	28.3	15.4
Northland	34.1	49.4	63.9	15.5	31.7	21.1
South Canterbury	33.1	46.8	61.2	14.8	30.6	17.6
Southern	29.4	42.2	60.9	12.3	27.0	16.1
Tairawhiti	37.3	50.0	64.4	14.9	31.1	24.5
Taranaki	31.5	45.3	62.7	13.6	28.6	17.1
Waikato	35.2	49.9	65.0	15.6	31.8	20.2
Wairarapa	32.1	45.3	62.6	14.6	29.6	17.5
Waitemata	24.3	40.5	63.8	12.8	23.8	14.5
West Coast	31.8	44.4	62.4	14.0	29.3	16.1
Whanganui	34.5	47.7	64.6	15.0	31.0	20.2

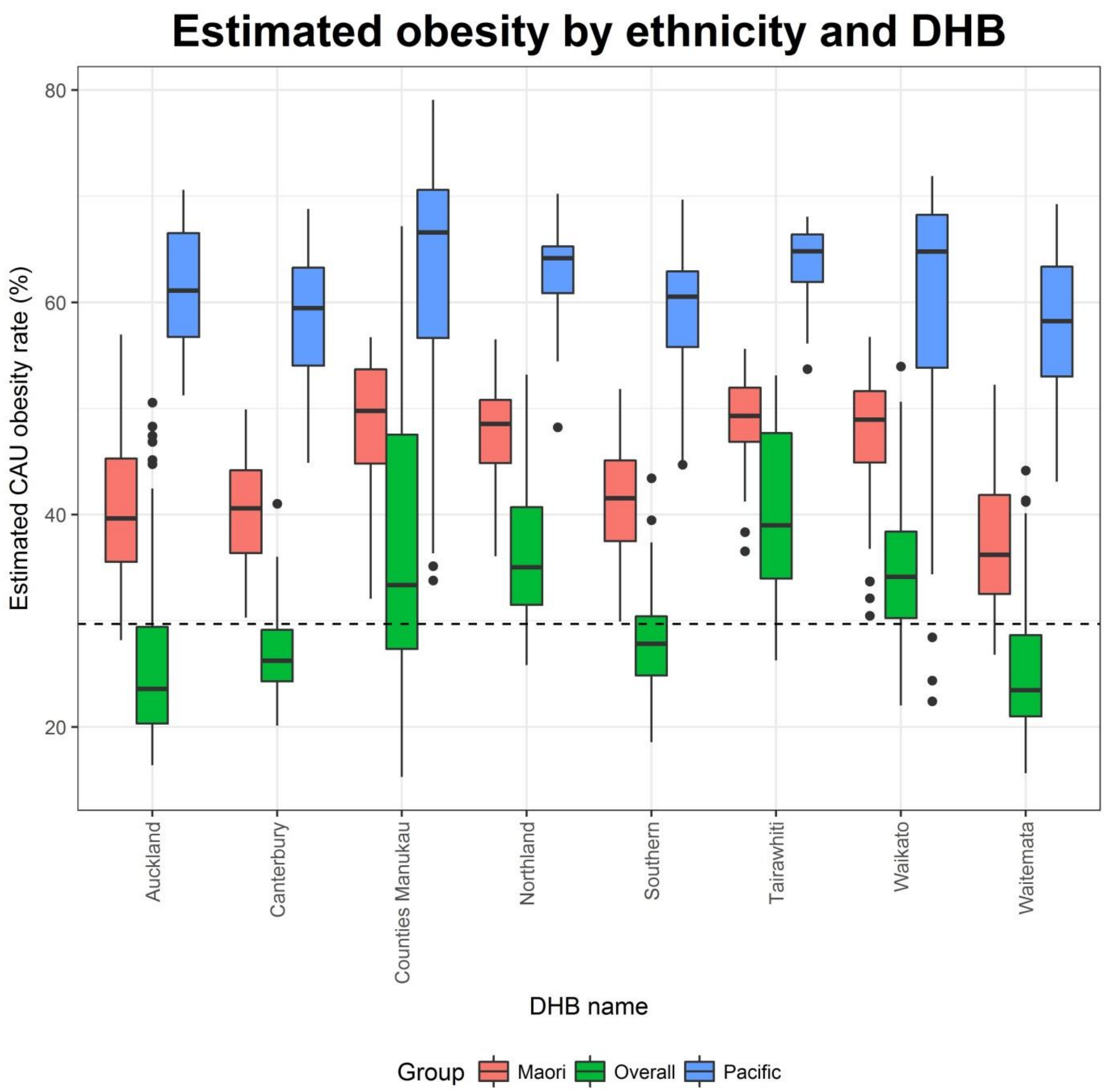


Figure 5.19: Spread of estimated obesity rates by ethnicity and DHB for selected DHBs. The dotted line represents the overall national obesity rate.

5.2.5 Case studies

The approach to subpopulations defined by a single variable described in the previous section can also be extended to create chloropleth maps for intersecting groups. Examples include Māori aged 15-24, or women aged 55-74, depending on which groups are relevant to the outcomes of interest. This is an important use of SMSM as obtaining information about small sub-populations can be very difficult using traditional data sources due to issues with sample size or confidentiality.

Figure 5.20 shows an example of older adults (age 50+) who are physically inactive (do not meet the recommendation of 150 minutes of moderate to vigorous physical activity per week) and are obese. Figure 5.20 shows that obese older inactive adults are concentrated in urban areas and are much less common in rural areas.

Intersecting subpopulations can also be used to identify ‘target areas’ for a particular policy or intervention. To do this, thresholds are set for a combination of variables, and potentially a minimum population threshold as well. There are many possible permutations of this, which can be adjusted as needed for the policy context at hand.

Figure 5.21 provides an example which targets young (age 15-24) Māori in areas with high rates of obesity and overweight amongst this group (> 55% combined). The other two thresholds used were a minimum population size of 100 for this group and a high smoking rate among Māori (> 30% for all age groups). Overall Māori smoking rates were used to avoid small number problems in the Census data. This group was selected for this example because of the recently adopted Smokefree 2025 policy, persistently high smoking rates among Māori and the known association between smoking cessation and weight gain (Health Promotion Agency, 2016; Klesges et al., 1989; Ministry of Health, 2015a). Thus, it may be beneficial to provide additional support for obesity prevention among new ex-smokers, and this is one example of how SimAotearoa could provide support for decision making on this topic. This combination of factors identified high risk areas in parts of Northland, East Cape, Auckland (Tamaki, Otara, Mangere, Manurewa, Papakura, and Pukekohe), Lower Hutt (Naenae and Wainouiomata), parts of Porirua, and isolated areas of eastern and southern Christchurch (Figure 5.21).

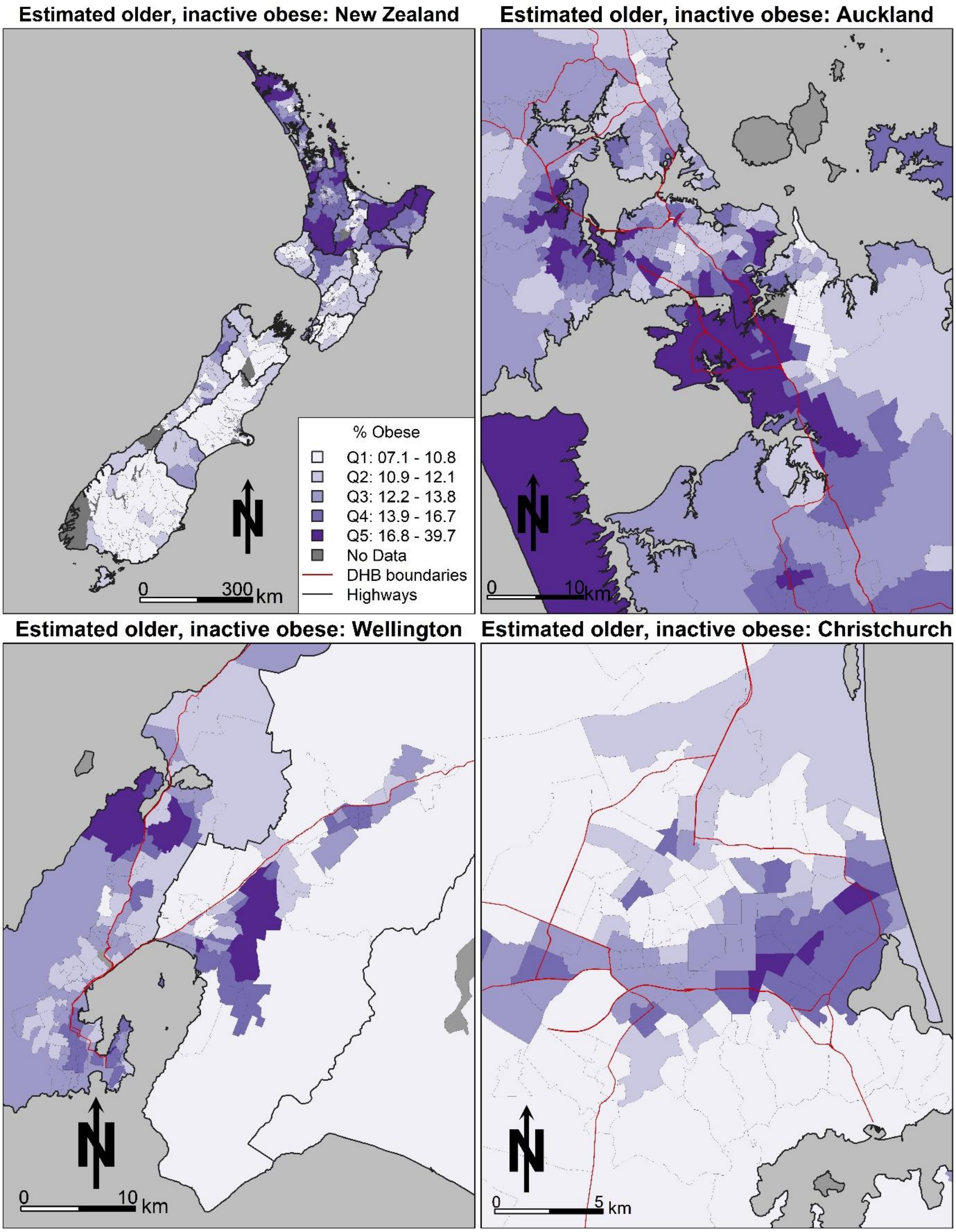


Figure 5.20: Estimated prevalence of obese individuals who are over age 50 and do not meet physical activity guidelines.

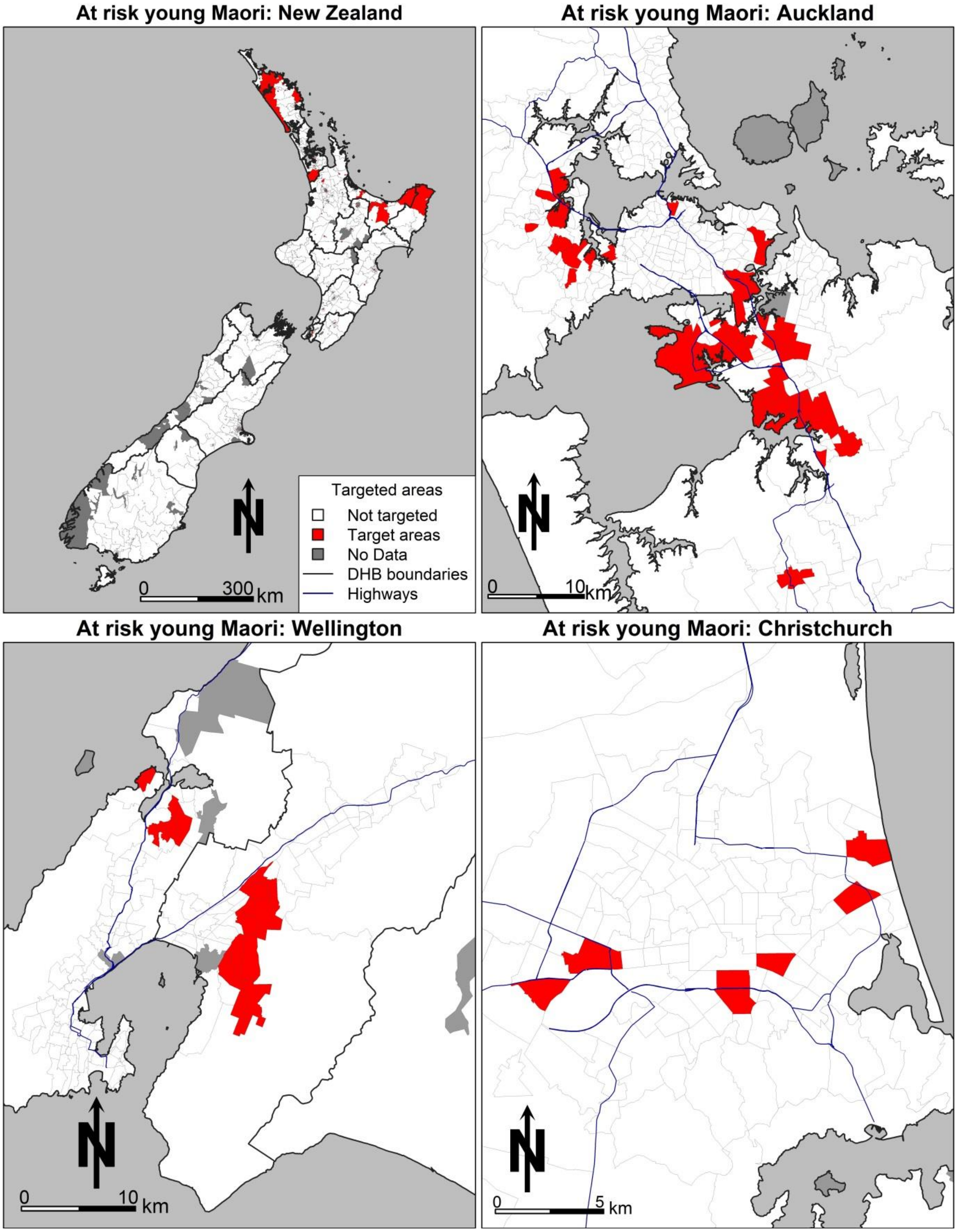


Figure 5.21: Areas identified as containing high risk young (age 15-24) Māori populations with high rates of obesity and smoking.

5.2.6 Area and deprivation comparisons

Comparisons between groups highlight disparities and inequities in the results. Here obesity rates are compared for the least deprived (Q1) and most deprived (Q5) areas (Figure 5.22). Graphs that include all five quintiles are available in Figure D.7, though the spread across all deprivation quintiles is more easily visible in a boxplot (Figure 5.23). It is very clear that there are substantial differences in the obesity rates predicted for these two different groups of areas, no matter which population or subpopulation is examined (Figure 5.22). Indeed, an ANOVA showed that the differences between deprivation quintiles were significant ($p < 0.001$). In particular there is a clear prevalence gap between the least and most deprived areas when considering overall obesity, as well as obesity in the three key sub-populations: Māori, Pacific Peoples and young people. The difference is less substantial, but still evident, for diabetes and combined obesity and overweight. What is also evident from this figure is that the range of estimated overall obesity rates (and estimated obesity in young people) is much wider in the most deprived areas than the least deprived areas. Using overall obesity as an example, all of the least deprived areas had obesity rates between 15.29 and 30.2%, with a mean of 23.4%. Conversely the most deprived areas had obesity rates ranging from 18.4% to 67.2%, with a mean of 41.9% (see Table 5.4).

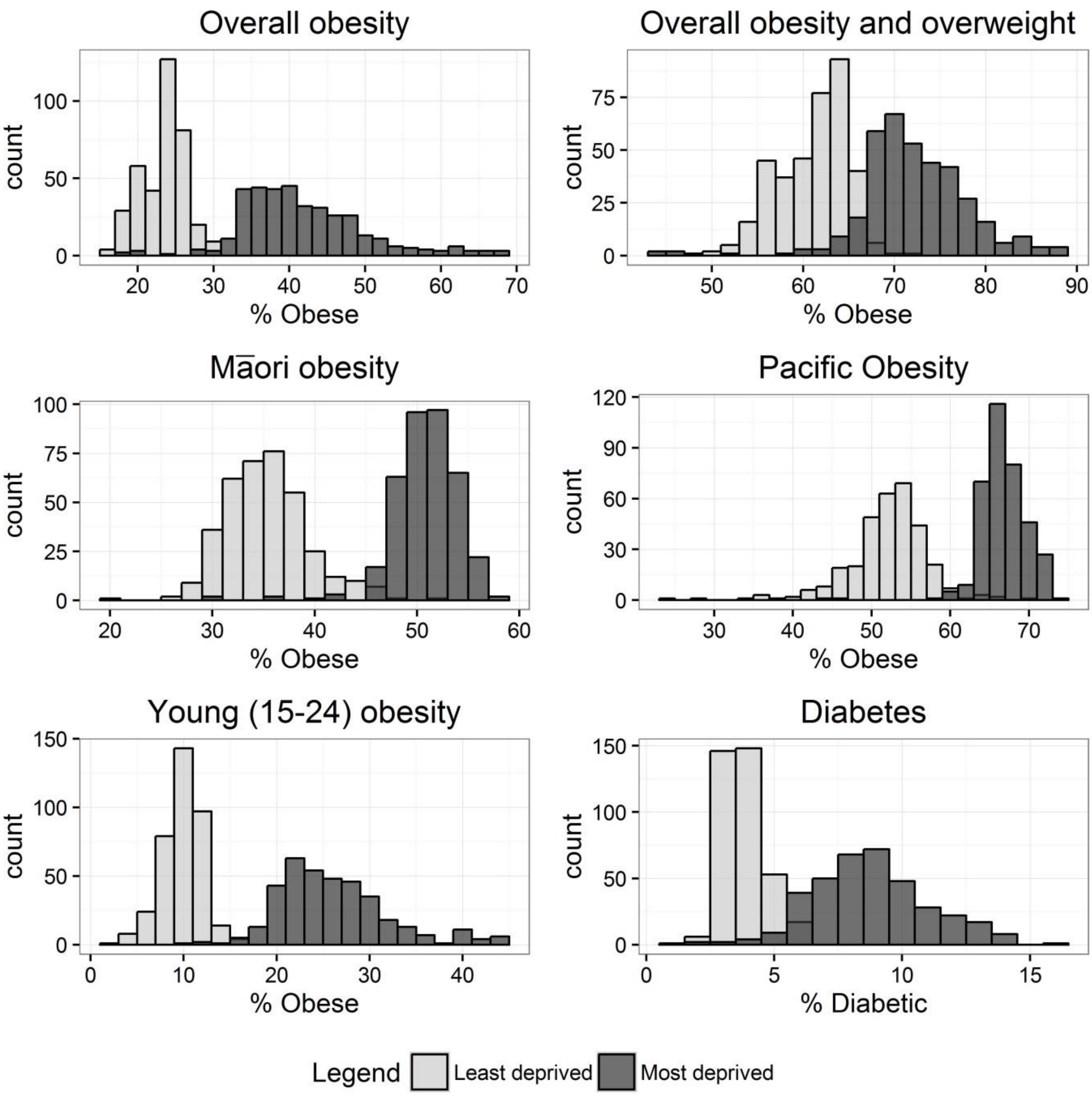


Figure 5.22: Comparison of obesity and diabetes rates between the least and most deprived CAUs

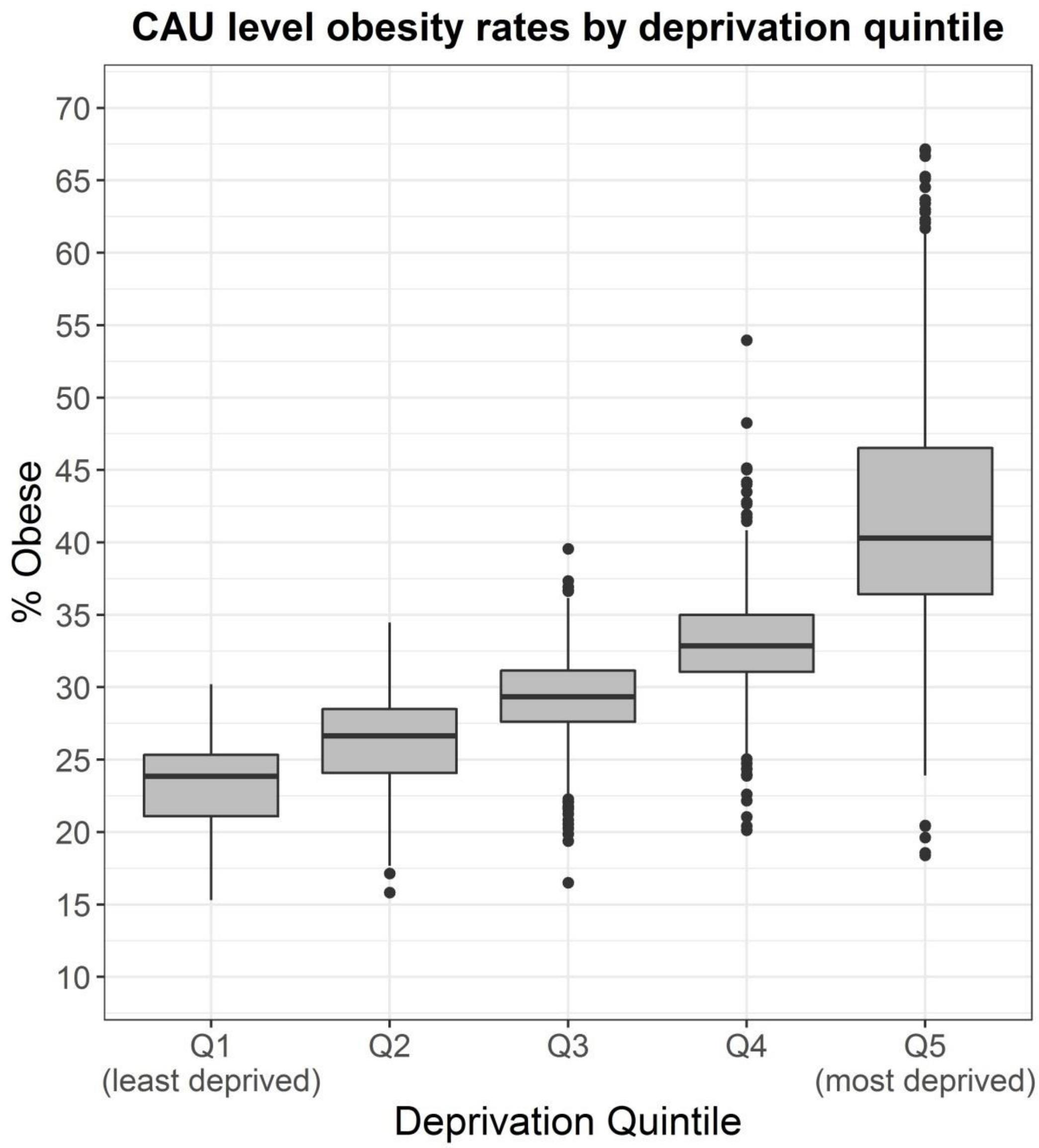


Figure 5.23: Boxplot showing the spread of CAU level obesity rates by deprivation quintile.

Table 5.4: Rates of obesity, overweight, and diabetes across deprivation quintiles and among selected population subgroups

	Obese	Overweight	Obese + Overweight	Diabetes	Māori Obese	Pacific Obese	Young Obese
	Quintile 1 — Least Deprived						
Minimum	15.29	33.32	48.77	1.64	20.57	24.37	2.93
Median	23.86	37.95	62.12	3.67	35.07	52.40	9.96
Mean	23.39	37.74	61.13	3.81	35.28	52.03	9.95
Maximum	30.20	42.25	71.94	6.26	51.85	69.26	16.90
	Quintile 5 — Most Deprived						
Minimum	18.39	20.19	43.24	0.88	29.92	44.70	10.66
Median	40.31	30.83	71.72	8.62	51.02	66.54	25.13
Mean	41.87	30.21	72.09	8.75	50.84	66.78	26.07
Maximum	67.16	35.56	87.83	15.68	58.52	73.64	44.72

This technique can also be used to examine differences between areas, and Figure 5.24 shows a comparison between Auckland and Counties Manukau DHBs. The differences here are less clear cut, but still visible. Overall obesity is skewed much more strongly towards the lower end of the spectrum in Auckland than in Counties Manukau, and to a lesser extent among Māori and for combined overall obesity and overweight. Results for Pacific Peoples, young people and diabetes suggest a pattern of lower rates in Auckland compared with Counties Manukau, but are much more equivocal as areas in both DHBs cover a similar range of estimated values.

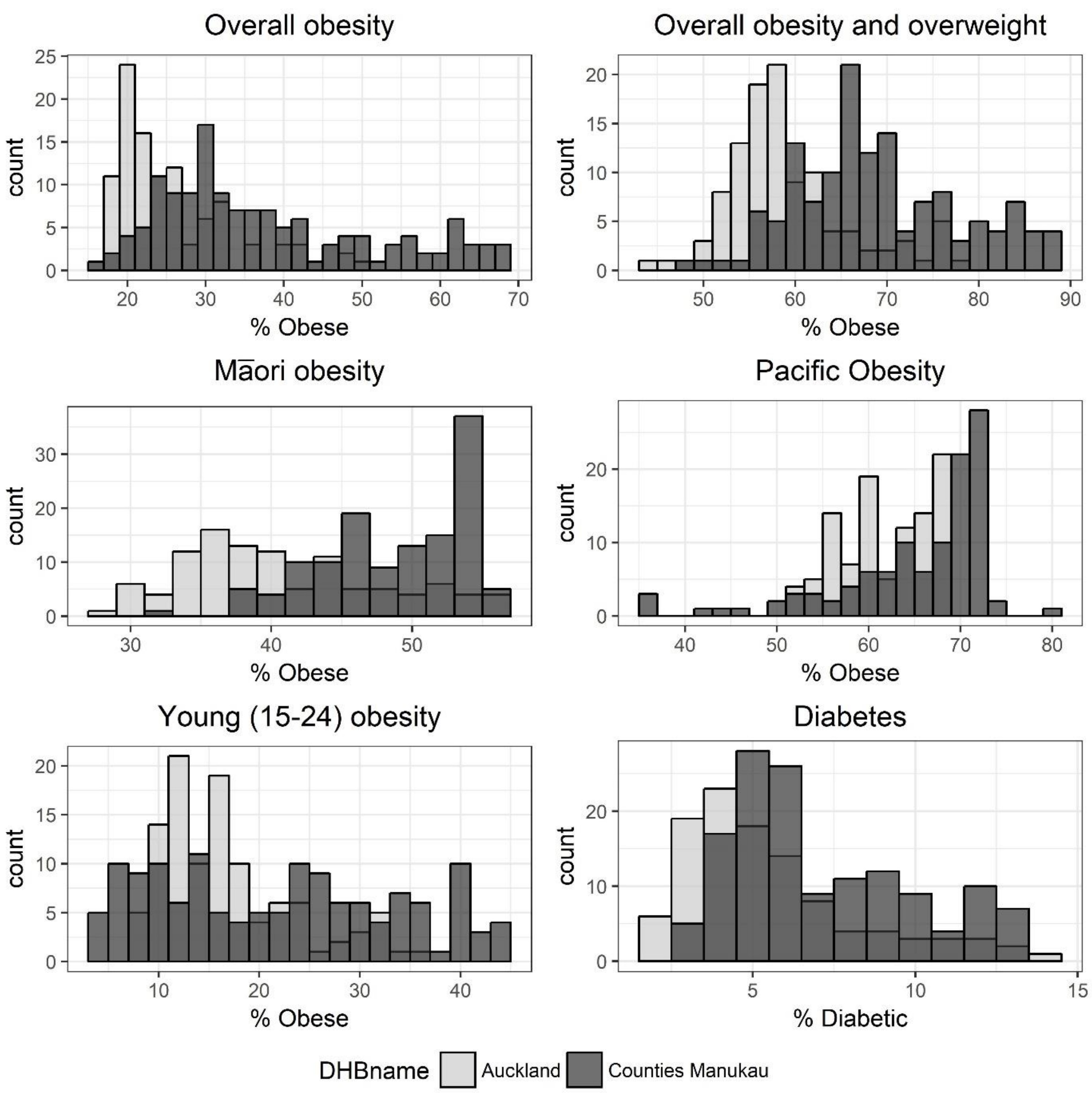


Figure 5.24: Comparison of obesity and diabetes rates between Auckland and Counties Manukau DHBs

The combination of these two together has the potential to be useful for policy making. For example, there are indications that obesity among Māori is sensitive to both the deprivation status of the local neighbourhood and some component of the regional, DHB environment as well; at least in the case of these two DHBs. However, for Pacific Peoples, young people and for diabetes, deprivation is important but DHB location is not (or at least, much less important). Taken alone, these results presented here do suggest that when making policy to combat obesity it may be more efficient to have a national strategy for Pacific Peoples and young people, but tailor any policy actions targeting Māori to specific DHBs. More detailed investigation including a larger number of DHBs would be required before this could be confidently utilised for policy purposes, but this suggests an avenue of future investigation.

The results presented in Figure 5.22 and Figure 5.24 echo and quantify the results presented in the maps above (Figure 5.12 through Figure 5.18). In particular, Figure 5.12 showed high rates of Māori obesity in the lower deprivation areas of East Tamaki and Howick, corresponding to higher rates of obesity among Māori in Counties Manukau relative to Auckland DHB. Conversely, spatial patterns for Pacific Peoples and young people more closely matched the overall pattern.

5.3 Discussion of main results

The previous section presented the outputs from SimAotearoa. The purpose of this section is to contextualise the results from the previous section.

This section will outline the limitations of the above results (Sub-section 5.3.1), discuss how the results are positioned in an international context (Sub-section 5.3.2), and address one of the key themes identified in the results: the divide between areas of high obesity and low obesity (Sub-section 5.3.3). The spatial clustering of obesity was evident across almost all of the results, though it was most obvious in Auckland. It also highlights the strong association between obesity, ethnicity and deprivation, and understanding this intersection is essential to understanding obesity in Aotearoa New Zealand.

5.3.1 Limitations of the main results

The nature of a SMSM is that it reflects the composition of the population in an area. Because individuals are given weights for all areas within the country or a set of similar DHBs, the model cannot reflect health effects that may be place specific. For example if individuals living near a fast food outlet are likely to have a higher BMI (though evidence for this assertion is equivocal e.g. Fraser & Edwards, 2010; Pearce et al., 2009), the model cannot capture the differences between otherwise identical areas which are close to fast food outlets and areas which are not close to fast food outlets. What is modelled in this example is the tendency for areas of higher deprivation to have greater geographic access to fast food outlets (Pearce et al., 2007a). This comes along with the complex amalgamation of factors that is NZDep.

The results presented above demonstrate that SimAotearoa provides reasonable and robust estimates of obesity in Aotearoa New Zealand (particularly Table 5.1). However, it is still a model. It is not a census, it cannot capture place-based effects on health (as described above), and the estimates are not an exact measure. What they are is a reasonable estimate based on the key determinants of obesity, one that demonstrably performs well in comparison to its international peers (Cataife, 2014; Edwards & Clarke, 2009; Koh et al., 2015; Smith et al., 2011). Any future measurements taken for a specific area would supersede these estimates. The strength of SMSM is that taking such measurements is expensive, time consuming and laborious. In this context, reasonable estimates, such as those provided by SimAotearoa, are a valuable tool; but they should never be considered an exact representation of reality.

As has been discussed elsewhere in this thesis (see Chapter 2), there is a confounding relationship between deprivation, ethnicity and BMI. To summarise this simply, Māori and Pacific Peoples show higher BMI values at the same percentage of body fat as a European person. On top of this, Māori and Pacific Peoples are also overrepresented among those living in the most deprived areas, which are associated with higher BMI values among all groups. Consequently, these two factors accentuate each other: Māori and Pacific Peoples have high obesity rates both because BMI overestimates obesity in these groups and because they are more likely to live in areas associated with high obesity. Caution should always be used when interpreting obesity estimates for Māori and Pacific Peoples, in this study or any other.

5.3.2 Aotearoa New Zealand in an international context

Estimates from SimAotearoa suggest that Aotearoa New Zealand has higher maximum obesity rates in small areas and a wider range of obesity rates among small areas than found in the six other SMSM models currently available in the international literature that focus on obesity (Cataife, 2014; Edwards & Clarke, 2009, 2013; Edwards et al., 2011; Koh et al., 2015; Procter et al., 2008). Specifically, SimAotearoa produced the highest obesity estimates for a small area, 67.2%, compared with the next highest estimate of 56.9% in Detroit (Koh et al., 2015). SimAotearoa also produced the widest range of obesity estimates among small areas from 15.3% to 67.2%, a range of 51.9%, compared with 0.0% to 42.9%, a range of 42.9% in Rio de Janeiro (Cataife, 2014).

The wide range of obesity rates described above could be an artefact of the way the model was developed to accommodate the much broader area and population used in this model, but the model estimates reflect current understandings of obesity, health in general, ethnicity, and

SES in Aotearoa New Zealand. Aotearoa New Zealand’s ethnic composition complicates the interpretation of any international comparison, but nonetheless, these are not statistics of which Aotearoa New Zealand should be proud. The wide range of small area obesity estimates speaks to a concerning level of health inequity in this country. The obesity rates calculated for large-scales — whether national or DHB rates — obscure the reality of this obesity burden in some communities, a textbook example of the modifiable areal unit problem (Openshaw, 1984a).

Among the international obesity SMSM models, SimAotearoa is the only one that specifically models obesity for an entire country, albeit one with a relatively small population. One model did include obesity as one of several variables of interest for Scotland, but this is still a subset of the UK (Campbell & Ballas, 2016). Modelling obesity across a country as heterogenous as Aotearoa New Zealand presented problems with differing population composition in different areas that were not experienced in other models, and is likely a key contributor to the necessity of subdividing the microdata as discussed in Sub-section 4.3.4. In terms of target population size, Detroit has the most similarly sized population to Aotearoa New Zealand at 3.86 million (Koh et al., 2015). Most other models examined specific cities (Cataife, 2014; Edwards & Clarke, 2009; Koh et al., 2015; Procter et al., 2008), thus in terms of the area covered, Northern England is probably the most similar as it covers a wide region including both rural areas and cities (Edwards & Clarke, 2013; Edwards et al., 2011).

The inclusion of subpopulations and diabetes in this analysis was novel compared to previously published work, as was the analysis of diabetes prevalence. However, several previous studies examined some part of the obesogenic environment (Cataife, 2014; Edwards & Clarke, 2009; Koh et al., 2015; Procter et al., 2008) which was not assessed here; this is a key area where the model could be developed in future. Several previous studies assessed deprivation, though methods used varied (Cataife, 2014; Edwards & Clarke, 2009; Koh et al., 2015; Procter et al., 2008).

This study reinforces the complex relationship between obesity and deprivation that has been highlighted by previous work (Edwards & Clarke, 2009). It adds further evidence that different parts of the population do not always follow the same overall pattern of obesity, consider the Pacific population in Sub-section 5.2.4. Additionally, these results support the possibility that SMSMs may struggle to fit accurate results for low obesity areas as has been found in other studies (Koh et al., 2015).

5.3.3 Two Aucklands? Spatial segregation of obesity

In Auckland and Wellington areas of high and low obesity rates were strongly clustered (see Sub-section 5.2.2), to the extent that the argument could be made that populations with high and low obesity rates are relatively segregated from each other. In urban parts of Auckland and Wellington in particular, there were areas of high obesity, and areas of low obesity, but very few areas in the middle range. Auckland is a city with many problems, including an extant housing crisis with many low income families struggling to afford the costs of accommodation (e.g. Bath, 2016; Howden-Chapman, 2015; Macfie, 2016; Nelson, 2016; Sergel, 2017). The results presented here suggest that Auckland is not merely a city with economic ‘haves’ and ‘have nots’, but also a city where health (in terms of obesity) is divided along socio-economic lines.

Given the strong spatial separation between high and low obesity areas, it is worth considering ethnic residential segregation as a possible explanation of obesity patterns, as well as the impact it could have on residents. Previous research has shown substantial residential segregation between ethnic groups in Auckland from 1991 to 2006 (Johnston, Poulsen, & Forrest, 2011), though Aotearoa New Zealand and Australia are generally considered to be less ethnically segregated than other similar countries, such as Canada, UK, and USA (Johnston, Poulsen, & Forrest, 2007). In Auckland, European populations have historically been clustered into areas with a homogenous ethnic profile, whereas Māori and Pacific groups were often found together (reducing their individual clustering), and those of Asian ethnicity were less clustered and more often distributed across many areas as a large minority (Johnston et al., 2011). Considering the obesity patterns in ethnic groups, the obesity patterns described in this chapter are consistent with previous research (and the distribution of ethnic groups in 2013 Census data, see 0), but ethnicity and deprivation are highly correlated and can be difficult to disentangle (Bécares, Cormack, & Harris, 2013; Harris et al., 2006a; Rush et al., 2009).

From a health perspective, ethnicity may be less important in terms of segregation than deprivation. Previous research found little evidence that highly segregated populations exhibited higher rates of smoking in Aotearoa New Zealand, with the relationship between segregation and smoking largely explained by deprivation (Moon, Barnett, & Pearce, 2010).

One potential future avenue of investigation is to better explore the interaction between ethnic spatial segregation and obesity in a similar manner to Moon et al. (2010). This may help to tease out the driving force behind strong correlation between ethnicity, deprivation and obesity and better explain the spatial separation discussed in this chapter. Alternatively, other underlying determinants of obesity, such as age, could also be investigated.

The results presented in this chapter have painted a consistent picture of residential segregation not only along ethnic lines, but also by body size. Thus, it is worth considering the potential impacts of anti-fat bias. In a study of health promotion efforts in Aotearoa New Zealand, Thompson and Kumar (2011) discuss the moral judgements that influence the behaviour of their participants towards individuals perceived as being 'healthy' or 'unhealthy'. Those who are not perceived to display the 'correct' behaviour may then be subject to different forms of discrimination (Thompson & Kumar, 2011), which is consistent with other research on different forms of discrimination faced by obese people (Longhurst, 2005; Puhl & Brownell, 2001; Saguy & Riley, 2005). This is further reinforced by Shapiro (2008, p. 5), writing about empathy and othering in medical students' education: *"We are not able to recognize ourselves as pure, healthy, and good unless we have someone whom we can identify as defiled, sick, and 'bad.'"*

No specific research could be found regarding the presence or absence of a spatial component to anti-fat bias. However, a cross-sectional study in the UK found, perhaps unsurprisingly, that normal weight participants had significantly stronger anti-fat attitudes than overweight or obese participants, and were also more likely to believe that obesity is controllable (Flint, Hudson, & Lavallee, 2015). If normal weight individuals hold similar strong anti-fat attitudes in Aotearoa New Zealand, then it is quite likely that anti-fat attitudes will also have a spatial component: less anti-fat bias in areas of high obesity and more in areas of low obesity. With some assumptions, degree of anti-fat bias could conceivably be mapped through the SMSM results in future.

The potential for a spatial component to anti-fat bias has implications for the interaction between socio-economic status, ethnicity, and obesity because of the strong correlation (both spatial and aspatial) between these three axes of social difference. Minority ethnic groups and those of lower SES are subject to significant moral judgement and discrimination, even without considering the additional impacts of body weight (Harris et al., 2012; Harris et al., 2006a, 2006b); the current evidence regarding the impact of obesity on the experience of discrimination by minority groups is currently fairly limited and equivocal (Harris et al., 2012). In addition to individual discrimination, areas and their residents may also be stigmatised (Keene & Padilla, 2014). Given that those most likely to stigmatise obesity are those with low body weight (who, logically have a lower likelihood of living in high obesity areas), this raises the possibility that particular areas may come to be perceived as ‘fat zones,’ and further contributing to the stigmatisation of residents and likely contributing to negative effects on their health. It may be argued that this has already taken place, as the high concentration of obesity in certain areas is already widely acknowledged in Aotearoa New Zealand (Baker-Wilson, 2016; Dastgheib, 2014; Galler, 2017; Johnston, 2013).

The presence of two different Aucklands, one with a high burden of obesity and the other with a low burden, occupying the same narrow isthmus raises questions that reach far beyond individual, or even public health effects. Though the correlation between SES, ethnicity and obesity in Aotearoa New Zealand is already well established (Ministry of Health, 2015a), this chapter highlights that these three intersect, not just in particular people, but in particular *places*. Therefore, it could be argued that geography matters, when it comes to obesity. Disadvantages along social, economic, and health dimensions are confined to relatively small areas of the country; these effects can interact in ways that may not always be obvious (Rosenthal & Lobel, 2011; Viruell-Fuentes, Miranda, & Abdulrahim, 2012). Any policy which does not account for this is much less likely to be effective.

5.4 Summary: The utility of spatial microsimulation modelling

The purpose of this chapter was to address the static model part of Objective 4: to explore the results of both static and projected spatial microsimulation models for obesity, diabetes, and key population subgroups, including how these results may be potentially relevant to policy. This chapter has demonstrated the ability of SMSM to supply specific estimates for obesity and related conditions for CAUs and DHB results that are consistent with NZHS estimates. These results have been further examined to assess the distribution of obesity and related conditions in relation to several other considerations: deprivation, population subgroups, and identifying ‘high risk’ areas. Further, the results have been analysed to assess the congruence between deprivation and obesity estimates, and conduct cluster analysis. Most of the above features have been mapped.

Key results highlighted in this chapter include (1) further illustrating the importance of deprivation as a key component of obesity in Aotearoa New Zealand, and additionally the very substantial health gap (in terms of body weight) between areas of high and low deprivation across all subgroups. (2) The very strong clustering of obesity into a limited subset of areas, particularly: Northland, South Auckland, Waikato, East Cape, Porirua and Lower Hutt. (3) that population subgroups do not always follow the overall spatial pattern, for example Māori show disproportionately high obesity rates in some lower obesity areas, and additionally in Pacific Peoples and young adults (15-24) there is less of a clear separation between high and low obesity areas the way there is in the general population.

These results reinforce the need to address a number of problem areas with respect to obesity in Aotearoa New Zealand. More specifically: (1) it is important to target inequity and social deprivation as an anti-obesity measure. (2) It may be beneficial to target specific sub groups, particularly Māori, Pacific Peoples and young adults in deprived areas. (3) High risk areas that may benefit from additional support or targeting may include parts of otherwise relatively low obesity DHBs, these areas should not be excluded from consideration. (4) Further research is needed on the health, social, and place-based effects of living at the intersection of low socio-economic status, minority ethnicity (primarily Māori and Pacific ethnicities), and obesity. These measures may already be in place, or may have been recommended by other research.

This chapter has also demonstrated how SimAotearoa is able to supply important evidence for Aotearoa New Zealand policy makers. SimAotearoa provides the following utility to policy makers: (1) specific estimates by CAU for obesity, severe obesity, overweight, and diabetes. (2) Specific estimates by CAU for the above conditions within any population subgroup in the NZHS, or combinations of these within realistic limits. (3) Tools to assess locations with respect to obesity related policy decisions. (4) A potential future tool to assess progress against obesity goals at a finer scale than DHB level, once 2018 Census data and 2016-19 NZHS data become available.

Chapter 6 Projecting estimated obesity rates in 2018 and 2023 with SimAotearoa

Chapter 4 presented the design and validation of SimAotearoa, while Chapter 5 presented the current time (2013) estimates generated by SimAotearoa. These two chapters demonstrated that SMSM can be a powerful tool for understanding obesity in Aotearoa New Zealand. While it is interesting to investigate current (or recent past) obesity rates, realistic estimates of future obesity rates are more important, in some respects. Estimating future need for health services is a key part of planning for adequate infrastructure to provide those services and for this reliable population projections are needed (Bongaarts & Bulatao, 2000; Harding, Vidyattama, & Tanton, 2011).

The purpose of this chapter is to further develop SimAotearoa and present obesity projections for 2018 and 2023. The projections and analysis presented here will address Objective 3: to develop a spatial microsimulation model (SimAotearoa) that estimates future adult obesity rates based on 2018 and 2023 population projections; and to test the validity of this model. Additionally, the projected portion of Objective 4: to explore the results of both static and projected spatial microsimulation models for obesity, diabetes, and key population subgroups, including how these results may be potentially relevant to policy.

This chapter is laid out as follows: firstly, different methods that can be used to produce population projections using SMSM are discussed in Section 6.1. The selected methodology is discussed in more detail in Section 6.2. The model results, including the validation, are presented in Section 6.3. The key findings are discussed in Section 6.4, along with the limitations of the model and future research directions. Finally, Section 6.5 summarises the key findings of this chapter and the possible uses of the results.

6.1 Introduction to population projection with spatial microsimulation

Models that estimate future population characteristics and needs are a key part of policy and planning at all levels of government, despite the inherent uncertainty involved in trying to predict something which has not yet happened (Bongaarts & Bulatao, 2000; Statistics New Zealand, n.d.-b). Statistics New Zealand provides population projections by age and sex at

CAU scale, along with national and regional ethnicity estimates and national labour force estimates (Statistics New Zealand, 2015b). SMSM can enrich these data sets by providing spatially disaggregated (i.e. CAU scale) estimates of population characteristics that are less easily projected (e.g. health variables such as obesity). SMSMs are able to utilise a diverse array of methods in order to estimate future populations, examples of projected models include SVERIGE (Rephann & Holm, 2004), SMILE (Ballas et al., 2005b), SimBritain (Ballas et al., 2005a), Moses (Wu & Birkin, 2013), SimEducation (Kavroudakis, Ballas, & Birkin, 2013), and SpatialMSM (Vidyattama & Tanton, 2013). Both the small area constraint tables and the micro data (through the SMSM process) need to be projected forward in time.

Methods available for generating SMSMs projected populations fall into two broad types: static or dynamic aging methods (Dekkers, 2015). The key difference between these two types of methods is the approach to 'aging' the population (the micro data) forward in time (Vidyattama & Tanton, 2013). Static aging methods take current microdata and apply it to projected future population composition (projected constraint tables) just as a fixed-time model would; the characteristics of individuals in the microdata set do not change. Examples of static aging models include SpatialMSM (Vidyattama & Tanton, 2013) and SimBritain (Ballas et al., 2005a). Dynamic aging methods change the microdata set by attempting to predict life course events such as birth, study, or change in health status — though probabilities of these events must be based on current data and generally assume no change. Examples of dynamic aging models include SVERIGE (Rephann & Holm, 2004), SMILE (Ballas et al., 2005b), Moses (Wu & Birkin, 2013), and SimEducation(Kavroudakis et al., 2013).

The purpose of this introductory section is to discuss the available methods for population projection with SMSM. The section will begin by describing static aging methods (Sub-section 6.1.1), before describing dynamic aging methods (Sub-section 6.1.2). Next, what is currently known about future populations will be described (Sub-section 6.1.3), before the section concludes by explaining the methodology that will be used later in the chapter and the rationale for that decision (Sub-section 6.1.4).

6.1.1 Static aging methods

Microdata weight inflation is the simplest possible method of projecting a SMSM model. This was the first type of future SMSM investigated by Vidyattama and Tanton (2013) using SpatialMSM. The method adjusts the weights from the 'base' static SMSM until they match the official population projections for age and sex (Vidyattama & Tanton, 2013). It does not control for any changes in the population other than age and sex, and is also unable to model long term trends that involve a change in the underlying population. This is because the method assumes that the relationship between the age and sex in the population and other variables of interest remain constant over time and that only population size changes (Vidyattama & Tanton, 2013). For example, there may be a trend away from car ownership among younger adults, but the model cannot capture any change in circumstances or preferences that may be causing this.

A slightly more sophisticated method is called static aging,[31] which is able to model projected future populations more accurately, but still experiences the same inability to model long term trends in the population variables. This method produces projected constraint tables separately for each variable in the model and then reweights the existing microdata to these instead of current Census tables (Ballas et al., 2005a; Vidyattama & Tanton, 2013). Both SimBritain (Ballas et al., 2005a; Ballas et al., 2007a) and SpatialMSM (Vidyattama & Tanton, 2013) use different methods to generate the projected constraint tables. The projected constraint tables are able to use both the small area projections for age and sex, along with any other projections available at larger scales (such as the regional ethnicity and national labour force projections available from Statistics New Zealand). Returning to the car ownership example, rates of car ownership may change if, for example, a change in another variable (such as SES) changes the number or composition of young adults in the model (e.g. increasing the number of low SES young adults who may be unable to afford a car). Conversely, weight inflation can model changes in car ownership only if the change results from the age or sex composition. Consequently, this method is superior to the weight inflation method as it better (though still imperfectly) captures changes in the population through estimating changes in variables other than age and sex.

Each of the two methods described above can be used independently, but they can also be combined. Vidyattama and Tanton (2013) describe a third static method utilising combination of the weight inflation and static aging methods for where there are only a small number of areas in the model. The specific scenario this combined method could address is one that appears to be specific to the GREGWT methodology used in SpatialMSM. GREGWT relies

[31] Not to be confused with the broader group 'static aging methods' which includes other methods for static aging of the population

on a generalised regression model to construct population estimates, and without a sufficient number of points (i.e. areas), the regression model will be unreliable (Vidyattama & Tanton, 2013). SimAotearoa uses IPF rather than GREGWT and therefore is not subject to this limitation. Additionally, the combined method is more difficult to validate, thus static aging is preferred where possible (Vidyattama & Tanton, 2013).

The main strengths of static aging methods are that they are simple and computationally efficient (Dekkers, 2015). Additionally, for the purposes of SimAotearoa, they can be built using a specific age range (i.e. adults over 15) by adjusting the coverage of the projected constraint tables. The key weakness of static aging is that it assumes that the current microdata are a suitable approximation of future individuals (Dekkers, 2015). If this assumption can be met, then the efficiency of static methods is preferable. If this assumption cannot be met, then it is necessary to use dynamic aging methods which are more complex.

6.1.2 Dynamic aging methods

Dynamic aging models generate a base synthetic population, then use Monte Carlo simulation to age and change the population based on estimated probabilities of various life course events such as birth, death, or migration. Examples of dynamic aging models include SVERIGE (Rephann & Holm, 2004) and SMILE (Ballas et al., 2005b). Returning again to the car ownership example: the probability of car ownership that is set by the model may be a constant value, or it may start as a low probability in the late teens and increase into the mid-twenties. There may also be a probability of losing car ownership, particularly from age 75, when additional proof of fitness to drive is required (New Zealand Transport Agency, 2016). This generates a much richer picture of the modelled population than static aging methods. And, importantly, dynamic aging is capable of modelling changes in the underlying population. The drawback to this increased detail is that the model is much more complex.

Projected models are only as good as the population projections or the probabilities of life course events (e.g. birth of a child or purchase of a car) used to generate them. If the population estimates or probabilities are inaccurate, the projected SMSM will also be inaccurate. In Aotearoa New Zealand, for example, birth rates vary by ethnic group as well as by age (Statistics New Zealand, 2013f). If the available data on birth rates is not disaggregated by age and ethnicity, the model will be less accurate because birth rates in some groups will be overestimated, and in others it will be underestimated. This can lead to large differences in the estimated number of new members of each subgroup, which has consequences for the results of later time steps in the model.[32] These differences among population subgroups should ideally be reflected in the model, as the interaction between subgroup population size and differential probabilities can change model outcomes and thus influence model accuracy. Additionally, both static and dynamic aging methods are more difficult to validate than 'current' models as there is no external data against which they can reasonably be compared.

One drawback to using a dynamic aging method is that these are inherently stochastic (though the base model may not be) and require an integerised synthetic population (Lovelace & Ballas, 2013). Integerisation slightly decreases the accuracy of the model, and is not necessary unless integer outputs are required for a subsequent analysis, like dynamic aging. So far, SimAotearoa has avoided using stochastic methods as the predictability of a deterministic model is generally more useful for policy analysis and future service provision planning (see Sub-section 4.2.5).

Another drawback to dynamic aging methods is that it is more important to model individuals within households — a level of complexity lacking in the existing version of SimAotearoa. The reason for this is that household composition is likely to affect the probabilities of life course events used to model future time periods. For example, a single person is much less likely to have a child than a couple, assuming that all are of child-bearing age.

6.1.3 Existing information about future populations

Official population projections can give us important information on how obesity may vary in future. It is important to identify these in advance, so that their impacts on the SMSM can be assessed. Key demographic changes are the increase in non-European ethnic groups, the increase in individuals identifying with more than one ethnic group and the aging of the population (Bascand, 2012).

[32] Consider a synthetic population with 1000 women, all of whom are partnered and of reproductive age. Group A contains 700 individuals and 10% of these give birth to a single child in this time period, a total of 70 children. Twenty percent of the women in both groups B and C have a child in this time period, but group B has a population of 200, while group C has a population of 100; the number of new children added to these two groups is 40 and 20 respectively. In total, this amounts to 130 new children in this time period, with an overall birth rate of 13%. When this overall rate is applied to each of these groups, the number of children born in each group is 91, 26 and 13. This is a very different result, with consequences for model accuracy if there are differential health effects among these groups.

As ethnicity influences how BMI is interpreted (see Sub-section 2.1.4), changes in the ethnic composition of Aotearoa New Zealand may influence future obesity rates. In recent years, non-European ethnic groups have increased in size, while the Pākehā/New Zealand European group has decreased; a trend which is expected to continue (Khawaja, Boddington, & Didham, 2007). Generally speaking, Māori and Pacific ethnic groups tend to exhibit higher BMI (and thus more obesity when using WHO BMI cut-off values), whereas Asian groups tend to exhibit lower BMI (see Sub-section 2.1.4). How this trend may affect small area obesity rates will depend on how ethnically homogenous each area is. If people of similar ethnicity tend to keep to themselves, there may be increasing divergence in small area obesity rates; whereas if areas become more ethnically diverse, obesity rates may become more similar among small areas. Alongside the increase in non-European ethnic groups there has been an increase in the proportion of individuals identifying with multiple ethnicities, particularly amongst young people (Khawaja et al., 2007; Statistics New Zealand, 2016b). This would tend to suggest increasing similarity in obesity rates among areas with high diversity.

Another expected change in the population is the increasing age profile of Aotearoa New Zealand, as the 'baby boomer' cohort[33] grows older (Bascand, 2012; Statistics New Zealand, n.d.-a). BMI in individuals begins to decline from around age 60 (Elia, 2001) and obesity rates are fairly low in the over 75 age group (Ministry of Health, 2015a), thus the aging population may help to create a downwards trend in overall obesity rates in the medium term. There are, however, still concerns about potential comorbidities related to prior obese status (Wang, Colditz, & Kuntz, 2007).

6.1.4 Methodology selected

Static aging methods were selected for the projected model as dynamic aging would have required substantial additional data on life course event probabilities that was not available. Another factor in this choice was the relatively consistent obesity rates in recent years (Ministry of Health, 2012a, 2013b, 2014a, 2015a). This suggests that the current population is likely to be a reasonable proxy for obesity in the short to medium term, based on Dekkers' (2015) assessment of the two main types of simulated aging. Thus, static aging was selected as a relatively simple but robust way of generating estimates based on existing Statistics New

[33] Currently aged 51-70 according to Statistics New Zealand (n.d.-a).

Zealand projections. Importantly, official projections were available for all four of the variables that could practically be used in the model, though at varying scales.

Because static aging was selected for the SimAotearoa projections, the changes in estimated obesity rates will depend on changes in population composition. A shift in underlying obesity prevalence cannot be predicted from events like a change in policy which causes substantial behavioural change in the population and reduced or increased obesity rates. As mentioned above, the national obesity rate has remained static for the last few years (Ministry of Health, 2012a, 2013b, 2014a, 2015a); so this is a reasonable assumption for this model.

The key question addressed by the projected SimAotearoa model is: what happens to obesity if nothing changes? This assumes that underlying obesity rates do not change and that the constraint table projections are reasonably accurate. There is a further underlying question that can be asked once data from 2018 are available:[34] is obesity higher or lower than predicted by SimAotearoa? The reasoning behind this question is that the projected SimAoteaora model will reflect expected obesity given changes in the composition of the population, not changes in the underlying prevalence of obesity.

6.2 Projection methods

The previous section outlined the methods available for constructing a projected SMSM. This section will go into more detail describing the data and methods used for this projection.

The projected models presented in this chapter are based on the static aging methodology used by Vidyattama and Tanton (2013), though the methodology is similar to Ballas et al. (2005a). Constraint tables are projected to future years using existing population projections from an official data source. The SMSM is then constructed in the same manner as described in Chapter 4 (Figure 4.2), including the same microdata, but using these projected constraint tables instead of Census data. Finally, the model is checked and validated using several different procedures.

These steps will be outlined in more detail in the following four Sub-sections. First, the models which will be constructed are described (Sub-section 6.2.1), then the data that will be

[34] Likely in early 2019.

used (Sub-section 6.2.2). Next, the methodology will be discussed (Sub-section 6.2.3), followed by the validation processes (Sub-section 6.2.4).

6.2.1 Model building using projected data

A variety of models were constructed during the projection process, each with a different purpose. Firstly, the validation model, where 2006 Census data and 2013 ERP were used to model population characteristics in 2013. The next model is the base model which used the same data as the final 2013 model from Chapter 4, but was constructed without the deprivation variable. The base model will be used to estimate the change in obesity rates in place of the standard 2013 model (see Chapter 4) as the change in model construction would otherwise render comparisons difficult.[35] Consequently, the projected models are compared back to a base model without deprivation.

Deprivation has not been used as a variable in any of the models newly presented in this chapter because the smallest available scale for population projections is CAU; as the deprivation variable used in Chapter 4 relies on the interrelationship between MB and CAU scale populations, this variable cannot be projected. Finally, there are separate models estimating obesity rates in 2018 and 2023. In order to help distinguish between the different models, Table 6.1 shows the variables used in each model, the Census data used to generate projections or build the model and the time period for which it estimates obesity.

[35] In the same time period with the same data, there will be differences in the obesity estimates given by models which do use deprivation as a constraint and those which do not.

Table 6.1: Description of the different model and time periods.

Model name	Standard Model	Validation Model	Projected Base Model	Projected 2018 Model	Projected 2023 Model
Abbreviation	Std	Valid	Base	2018	2023
Chapter	Chapter 4	Chapter 5	Chapter 5	Chapter 5	Chapter 5
Time period for estimates	2013	2013	2013	2018	2023
Base census year used	2013	2006	2013	2013	2013
Constraint table source	Census	ERP	Census	Projection	Projection
Variables	Sex, Age, Deprivation, Ethnicity, Labour Status	Sex, Age, Ethnicity, Labour Status	Sex, Age, Ethnicity, Labour Status	Sex, Age, Ethnicity, Labour Status	Sex, Age, Ethnicity, Labour Status
Purpose	Estimate current obesity	Validate the projection	Provide a comparable base	Estimate obesity in 2018	Estimate obesity in 2023

6.2.2 Data

The area level constraint tables for the projected SMSMs are based on a variety of official data sources, described in Table 6.2. How they were used in the projected model is described in the next Sub-section 6.2.3. The chosen constraint tables were the most suitable of those available from Statistics New Zealand, but pose a few problems for the model. Firstly, the labour force projections were only available with a base of 2015, not 2013; this means that the labour force size estimated for the 2013 models was based on the 2015 labour force and needed to be scaled to the 2013 population size. Secondly, the data sets indicated as 'estimates' are based on the Estimated Resident Population (ERP) for 30 June of the given year. The microdata sample used in this chapter is the same 3-year NZHS sample used in Chapter 4 (n = 34955, see Sub-section 4.2.1).

ERP is based on the Census population count adjusted with official data on births, deaths and migration (Statistics New Zealand, n.d.-c). Consequently, ERP is generally more accurate than a population projection which must necessarily make assumptions about these key demographic forces (Statistics New Zealand, n.d.-b). However, ERP is not perfect, the ERP estimates for 2013 suggest more than 200,000 additional people in the country in the four months between the March Census count and 30 June (Statistics New Zealand, 2013e, 2016a); compared with a total population growth of just over 30,586 people per year for the previous 7 years (Statistics New Zealand, 2013e). This does not seem realistic. Even the period 2001 – 2006, which had much higher population growth, only exhibited a population increase of roughly 58,000 people per year (Statistics New Zealand, 2013e). The unrealistically high population projections for 2013 meant a relatively high error rate due to the discrepancy between Census and projected populations.

Table 6.2: Data sets used in the projected models, including year, variable and whether it is actual or estimated data

Use	Model	Scale	Type[36]	Year(s)	Based on	Variable(s)
Weight ethnicity and labour status projections	Valid, 2018, 2023	CAU	Census	2006, 2013	Actual data	Age by sex by ethnicity Age by sex by labour status
Constraint	Base	CAU	Census	2013	Actual data	Age, sex, ethnicity, labour status (singly)
Constraint	Valid	CAU	Estimate	2013	2013 ERP	Age by sex
Constraint	2018, 2023	CAU	Projection	2018, 2023	2013 Census	Age by sex
Ethnicity projections	Valid, 2018, 2023	TA	Estimate	2013	2013 ERP	Age by sex by ethnicity
Ethnicity projections	2018, 2023	TA	Projection	2018, 2023	2013 Census	Age by sex by ethnicity
Labour status projections	Valid, 2018, 2023	National	Estimate	2015, 2018, 2023	2015 ERP	Age by sex by Labour force status
Validation	Valid	CAU	Census	2013	Actual data	Smoking

6.2.3 Projected constraint tables

The process used to calculate the projected constraint tables for ethnicity and LFS is based on Vidyattama and Tanton (2013) and occurs in three stages: initial estimate, adjustment for

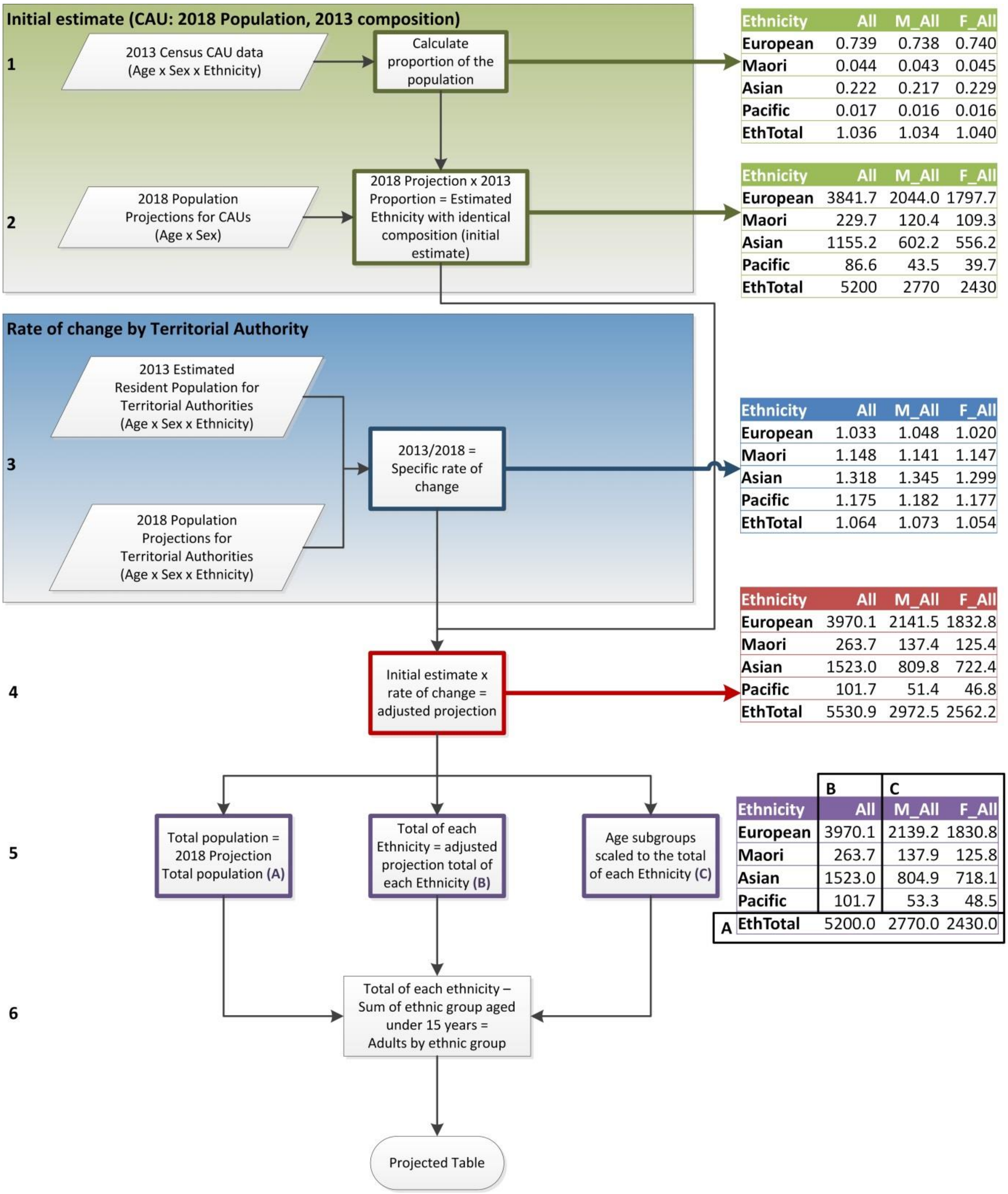
[36] All projections used were ‘middle’ or ‘median’ projections. Census data are collected in early March, population projections or estimates are for the population at 30 June of the given year.

projections, and adjustment to total. Once this is completed, children aged under 15 are removed, as SimAotearoa is focussed on adults. Modifications are made to the procedure for the time period and variable being predicted. As official projections were available for all four of the variables used, there was no need to use any of Vidyattama and Tanton's (2013) methods for constructing constraint tables for variables with no official projection.

This process is illustrated for the 2018 projection of the Ilam CAU in Christchurch (see Figure 6.1). The first stage of the projection process requires an initial estimate to be calculated. It begins with 2013 Census data in an age by sex by ethnicity table at CAU level (row 1 Figure 6.1). This is used to calculate the proportion of each ethnicity found within the CAU. These proportions are used to give initial estimates for each ethnic group based on the 2018 Statistics New Zealand projection of age by sex at CAU level (row 2 of Figure 6.1). This initial estimate is then set aside until later in step two.

For the next step of the projection, the estimates are adjusted based on the official projections for ethnicity. This uses territorial authority (TA) level projections of age by sex by ethnicity to calculate the specific rate of change in ethnic populations in TAs from 2013 to 2018 (row 3 of Figure 6.1). These TA level calculations are then combined with the initial estimates from step one, such that the initial estimates are adjusted for the rate of change (row 4 of Figure 6.1). All of the categories in this example became larger, but in some cases, the rate of change was below 1 and the initial estimate became smaller.

For the third and final step in the projection, the estimates are adjusted to known totals. Slightly different things happen to each part of the table for this step (row 5 of Figure 6.1). The population totals (A) are set at the same level as the total population from the 2018 CAU projection (row 2). The ethnicity totals (B) are set at the total for each ethnicity from the previous step (row 4), as each ethnicity is not exclusive with the others. The subgroups of each ethnicity (C) were adjusted to the total for the given ethnicity, so that the table added up in a sensible way, e.g. Male European and Female European should add to All European. The last required adjustment before the projected constraint table is ready for use is to remove children aged under 15 (row 6 of Figure 6.1). Estimates for LFS were generated in a similar manner, except that all parts of the table were scaled to the category totals (A) in the third step.



Ethnicity	All	M_All	F_All
European	0.739	0.738	0.740
Maori	0.044	0.043	0.045
Asian	0.222	0.217	0.229
Pacific	0.017	0.016	0.016
EthTotal	1.036	1.034	1.040

Ethnicity	All	M_All	F_All
European	3841.7	2044.0	1797.7
Maori	229.7	120.4	109.3
Asian	1155.2	602.2	556.2
Pacific	86.6	43.5	39.7
EthTotal	5200	2770	2430

Ethnicity	All	M_All	F_All
European	1.033	1.048	1.020
Maori	1.148	1.141	1.147
Asian	1.318	1.345	1.299
Pacific	1.175	1.182	1.177
EthTotal	1.064	1.073	1.054

Ethnicity	All	M_All	F_All
European	3970.1	2141.5	1832.8
Maori	263.7	137.4	125.4
Asian	1523.0	809.8	722.4
Pacific	101.7	51.4	46.8
EthTotal	5530.9	2972.5	2562.2

		B	C	
	Ethnicity	All	M_All	F_All
	European	3970.1	2139.2	1830.8
	Maori	263.7	137.9	125.8
	Asian	1523.0	804.9	718.1
	Pacific	101.7	53.3	48.5
A	EthTotal	5200.0	2770.0	2430.0

Figure 6.1: Procedure for projecting constraint tables, all examples come from a real CAU: Ilam in Christchurch.

Once the projected Census tables were satisfactorily constructed, the SMSM procedure used was exactly the same as that described in Chapter 4 (see Figure 4.2 and Sub-section 4.2.5). The same microdata set described in Sub-section 4.2.1 was used for all projected models.

6.2.4 Validation of the models

Validation processes for the projected models were similar to those described by Ballas et al. (2005a) as well as the validation methods used for the base model described in Chapter 4, but had a few key differences. Only 2013 models could be externally validated, as other time periods have not yet occurred and there is no "real, unconstrained data" available to compare these with. The primary purpose of the validation process was to establish that the method was reasonably accurate and did not involve selecting between possible candidate models to derive the 'best' model. The base model from Chapter 4 (where it was called the 'combined restricted data model') was assumed to be the best model for all projection scenarios. However, the projected models constructed here produce different results from the standard model due to the absence of deprivation.

The key validation process involved projecting 2013 constraint tables using 2006 Census results and 2013 ERP. Simulated smoking data from this model were then compared to 2013 Census results. Obesity rates were also aggregated to DHB level and compared to NZHS estimates. The model used for this was only used for validation of the method, the results from it are not used elsewhere. Key results presented in this chapter are the validation error from the Validation model, and the estimated change in obesity rates from the base model to 2018 or 2023.

6.3 Projection results

The previous section outlined the data and methods that will be used to construct the projected model. This section presents the construction of the model, its validation, and the results.

The fit, suitability, and results of the projected models were analysed in three key stages. First, the projected constraint tables are assessed for accuracy (Sub-section 6.3.1). Second, the results of the validation model, based on the 2006 Census, are examined to assess the suitability of the method (Sub-section 6.3.2). Finally, results for projected change in obesity will be presented for 2018 and 2023, including comparisons with the Base (2013) model (Sub-section 6.3.3).

6.3.1 Projected Census tables

When evaluating the accuracy of the model, it is important to first evaluate the accuracy of the projected Census tables. The projected age and sex tables are taken directly from Statistics New Zealand population projections and estimates, and can be considered to have the same degree of accuracy as these (Statistics New Zealand, n.d.-b, n.d.-c). The official projections and estimates do contain a degree of inaccuracy which is readily visible when comparing the ERP for June 2013 with Census data collected in early March of the same year (see discussion in Sub-section 6.2.2).

The constraint tables for LFS and Ethnicity were projected for this analysis, and consequently need to have their accuracy assessed. This can be done by comparing tables projected based on 2006 data to the 2013 Census (see Table 6.3 and Figure 6.2). The projected LFS constraint tables are fairly accurate: the employed category has been slightly over estimated, while unemployed and not in the labour force categories were slightly underestimated.

Ethnicity constraint tables are more difficult to calculate accurately. The method of projection initially generates inflated estimates, which are then scaled back to the actual population size. However, this is not possible with ethnicity as the nature of total response ethnicity dictates that the four categories do not sum to a single whole (refer to the discussion in Sub-section 4.2.3). Consequently, the four ethnic groups are overestimated (see Table 6.3 and Figure 6.3). The proportions that each ethnicity represents are fairly accurate, however, which is reflected in the lower ‘percentage of all responses’ part of Table 6.3. Here, the total of the percentages for each of the four ethnic groups were added together and each group is reported as a proportion of this total.

Table 6.3: Comparison of 2006 and 2013 Census data with projected constraint tables

	Census		Validation projection (2006 base)	Difference between projection and 2013 Census
	2006	2013		
Percentage				
Employed	65.0	62.3	65.2	+2.9
Unemployed	3.5	4.8	3.5	-1.3
NILF	31.5	32.9	31.3	-1.6
European	68.5	74.8	84.8	+10.0
Māori	12.1	12.4	14.8	+2.3
Pacific	5.5	6.0	7.6	+1.6
Asian	9.2	11.7	15.2	+3.5
Percentage of all responses				
Sum	95.3	104.9	122.4	
European	71.9	71.3	69.3	-2.0
Māori	12.7	11.8	12.1	0.3
Pacific	5.8	5.7	6.2	0.5
Asian	9.7	11.2	12.4	1.3

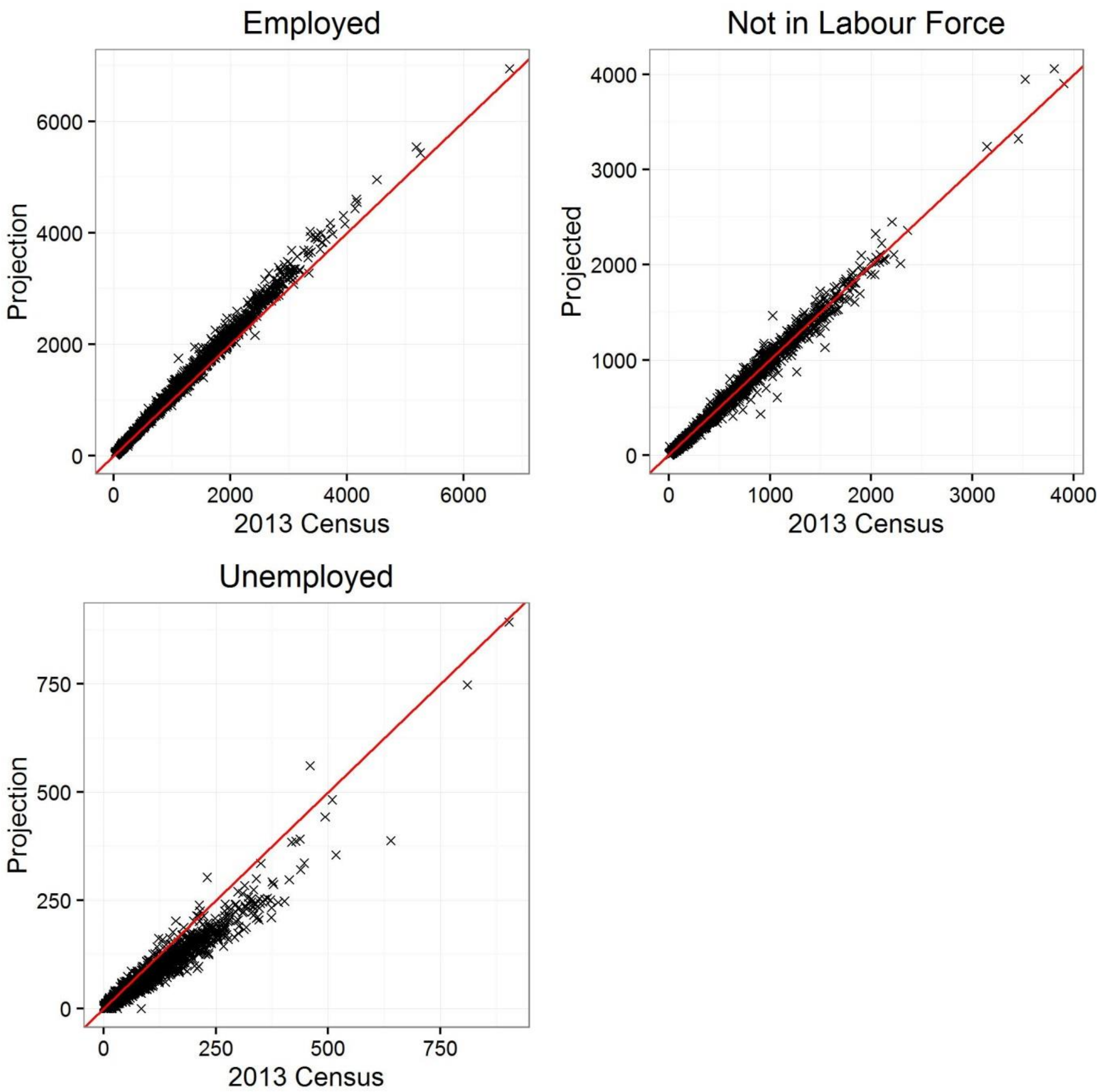


Figure 6.2: Comparison of projected Labour Status tables with Census 2013

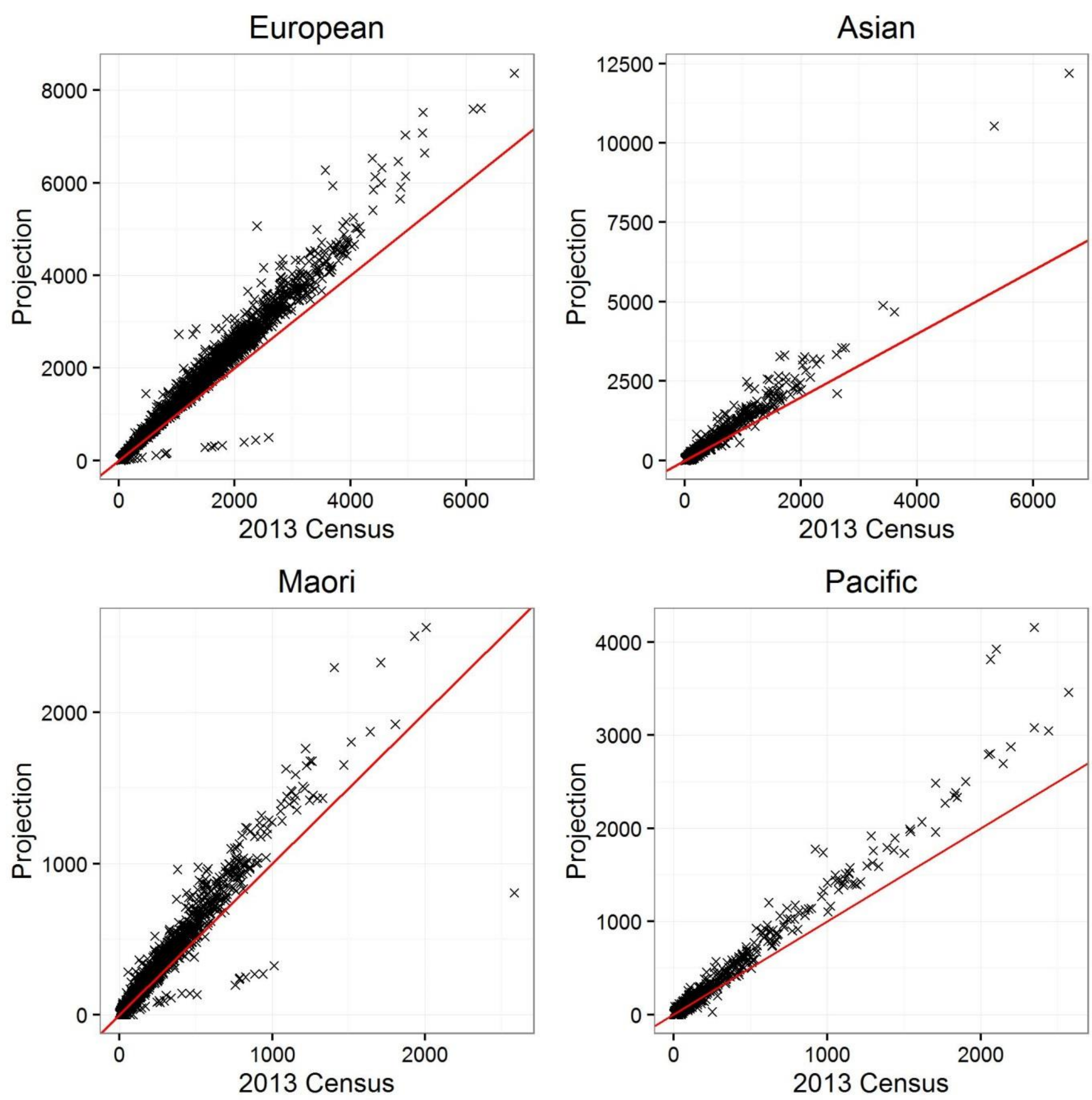


Figure 6.3: Comparison of projected Ethnicity tables with Census 2013

6.3.2 Validation: Projection from 2006

The quality of the projected SMSMs made with this method can also be evaluated by using 2006 Census data to generate projected tables for 2013 and comparing these to 2013 Census data. The purpose of the Validation model is purely to assess the validity of the method; it will not appear in subsequent results sections. Few extreme errors (> ±20%) were observed in Validation model (Table 6.4), and the model easily fits the usual SMSM rule of 80% of areas with less than 20% error. Table 6.4 also shows a comparison between the Validation model and the Standard 2013 model. The error estimates for the projected model are in most cases quite close to the same type of error for the standard model, and in some cases the projected model performed better. For example, the mean and median error for those who have never smoked is slightly lower in the projected model, though there is also a greater degree of spread between these two measures. The projected validation model can also be compared to Census totals (Figure 6.4) which indicates a reasonable degree of accuracy. Figure 6.4 exhibits a greater degree of dispersion of errors among CAUs in comparison to Figure 4.5.

Table 6.4: Summary of errors for the Projected Validation Model (based on the 2006 Census) compared with the Standard 2013 model from Chapter 4.

	Standard 2013 model			**Model projected from 2006**		
	Never	**Ex**	**Regular**	**Never**	**Ex**	**Regular**
Mean	5.60	3.31	3.29	5.55	4.61	4.98
Median	5.36	3.06	2.86	4.55	4.44	4.53
Spread	0.24	0.26	0.43	1.00	0.17	0.45
Std Error	0.10	0.07	0.08	0.14	0.07	0.12
Minimum	0.00	0.01	0.00	0.00	0.00	0.00
Maximum	39.22	21.59	21.57	59.26	23.14	44.52
TAE	201023	107016	109743	186006	164183	169416
% SAE >20%	0.38	0.11	0.11	0.86	0.05	0.27
R^2	0.99	0.97	0.93	0.99	0.96	0.81

Note: All values except the TAE line are based on the proportion of the total error.

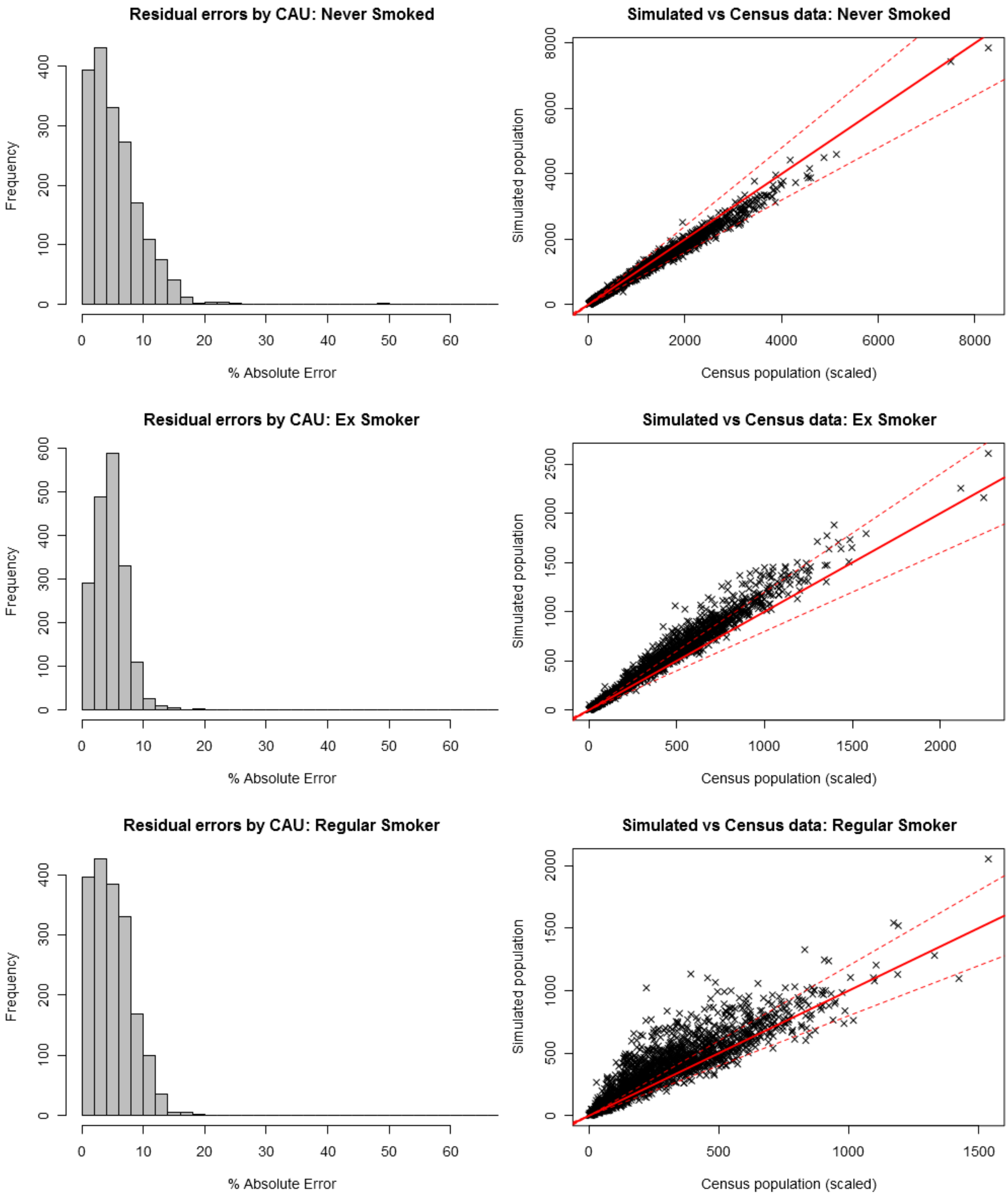


Figure 6.4: External validation error for the projected validation model (2013 estimates based on 2006 data)

When checking the performance of the projection, it is also useful to compare the obesity estimates for the projection to the obesity estimates from the standard model that has already been validated in Chapter 4. This comparison, seen in Figure 6.5, shows that the Validation model gave obesity estimates of around 30% for many more areas than the standard model. Where the standard model gave estimates ranging from around 22 to 38%, the projected model estimates were concentrated in the 28-35% range due to the absence of the deprivation variable from the projected model. Overall though, the two models are highly correlated (correlation coefficient 0.90).

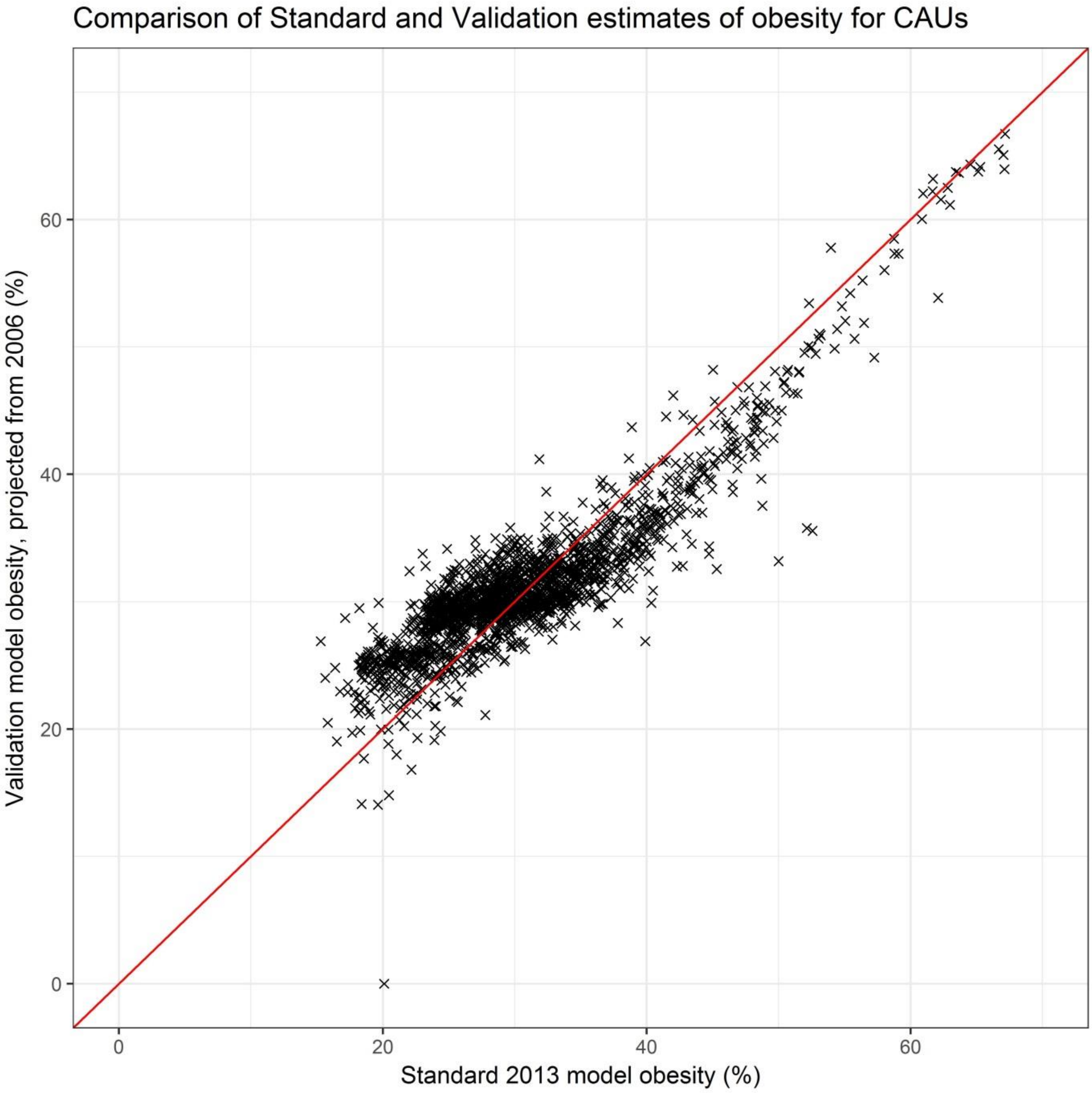


Figure 6.5: Comparison of obesity estimates from the Standard 2013 model and Projected Validation model

The smoking validation error for the projected validation model can also be mapped to detect any patterns in the error (Figure 6.6-8). The patterning of errors was similar to that observed in the standard model presented in Chapter 4 (see Figure 4.7, Figure 4.8, and Figure 4.9), though the level of error was slightly higher (overestimating smokers and ex-smokers and underestimating never smoked). Of note is that the model shows errors in the opposite direction from the overall trend in some areas of higher deprivation. For example, in Figure

6.6 smoking rates in eastern Christchurch were underestimated relative to the Census, whereas in most of Christchurch and Aotearoa New Zealand, smoking rates were slightly over estimated. This is most visible in Christchurch, and to a lesser extent in the Wellington Region and rural areas of the South Island; in Auckland, it is only noticeable for those who have never smoked. This patterning is only slightly evident in the standard model (compare with Figure 4.9), where it is exhibited in a smaller number of areas and to a lesser degree, conversely it is easily visible in the Validation model (particularly in Figure 6.6 and Figure 6.8).

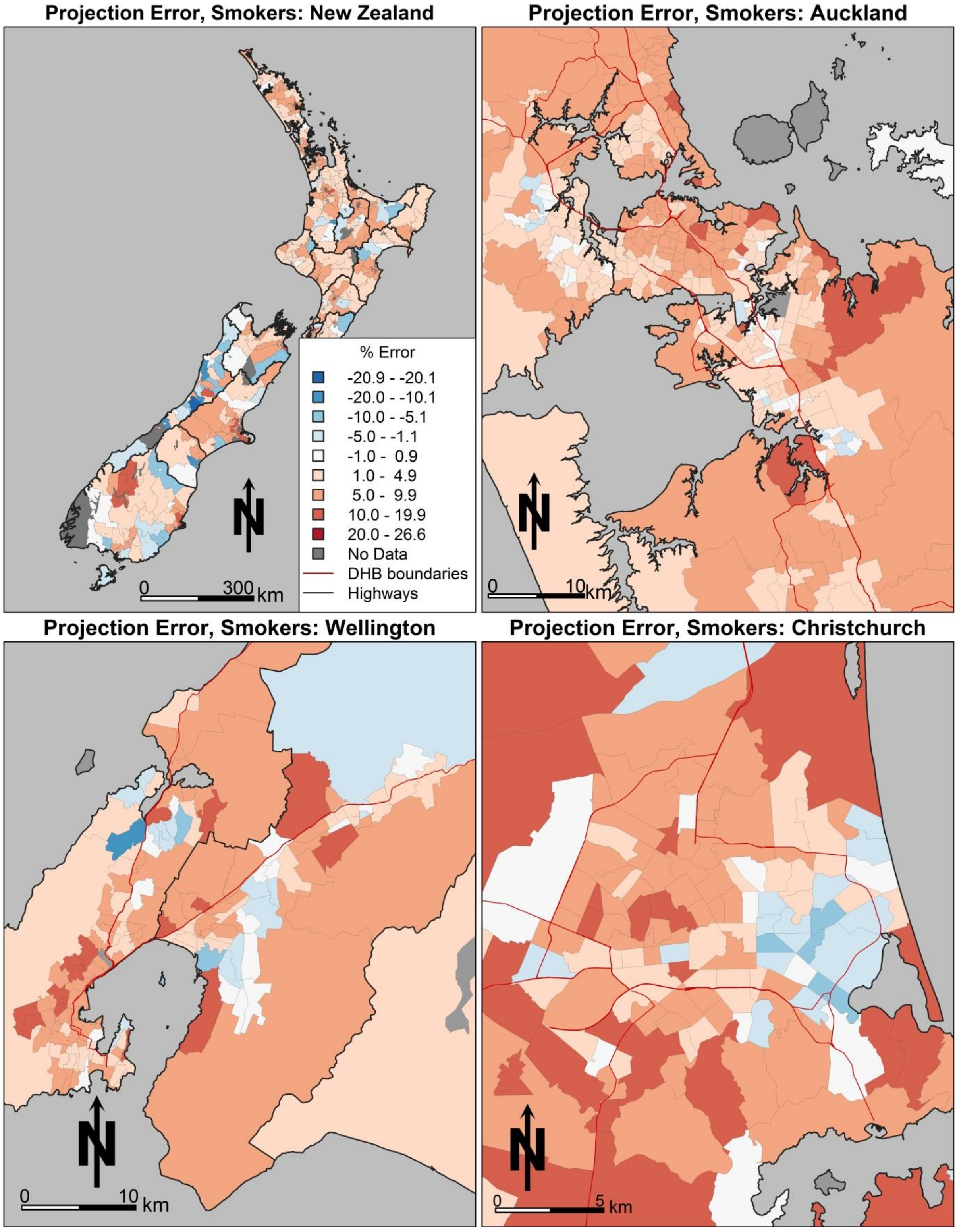


Figure 6.6: Errors for Smokers in the Projected Validation model for 2013 based on 2006 Census data

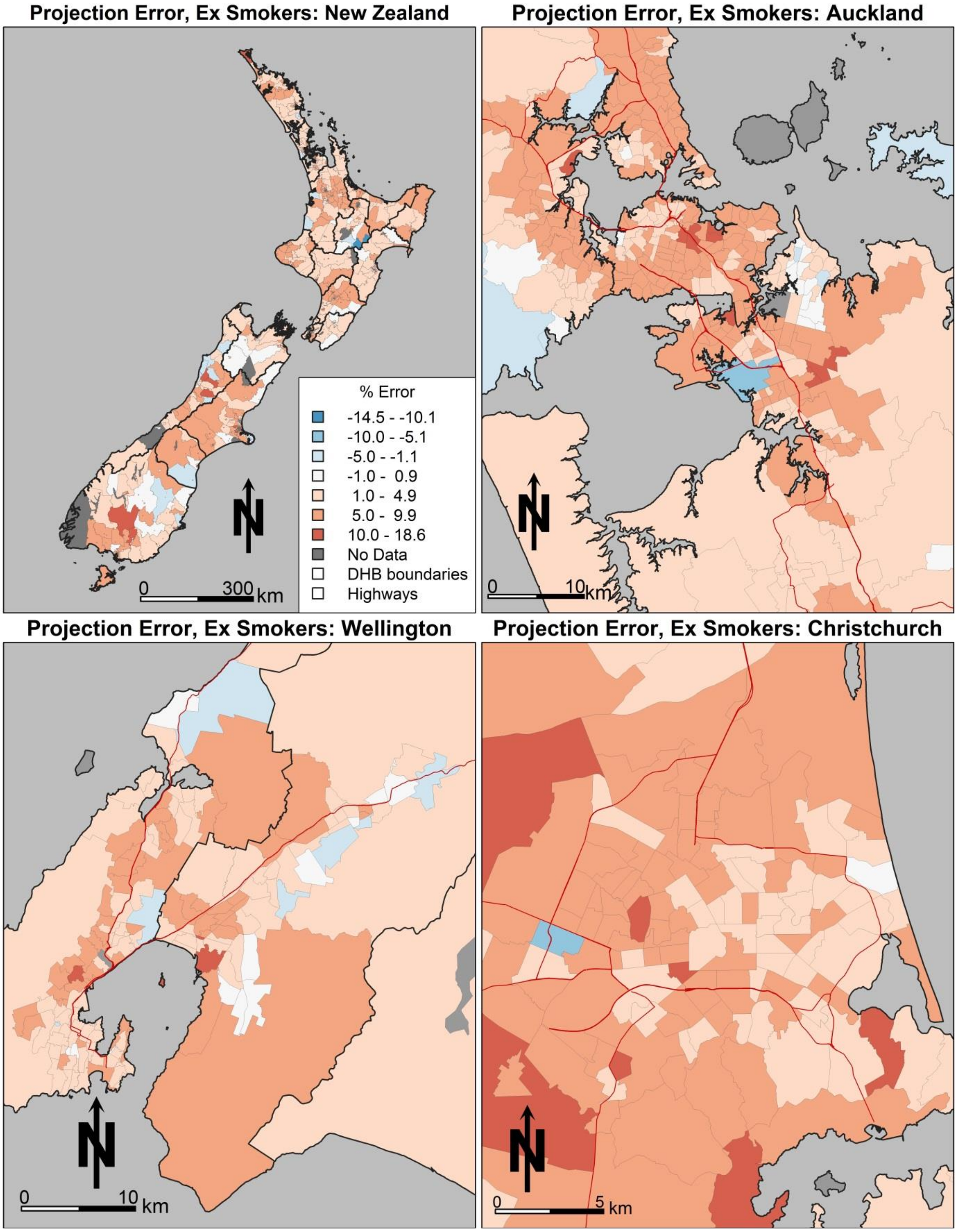


Figure 6.7: Errors for Ex-Smokers in the Projected Validation model for 2013 based on 2006 Census data

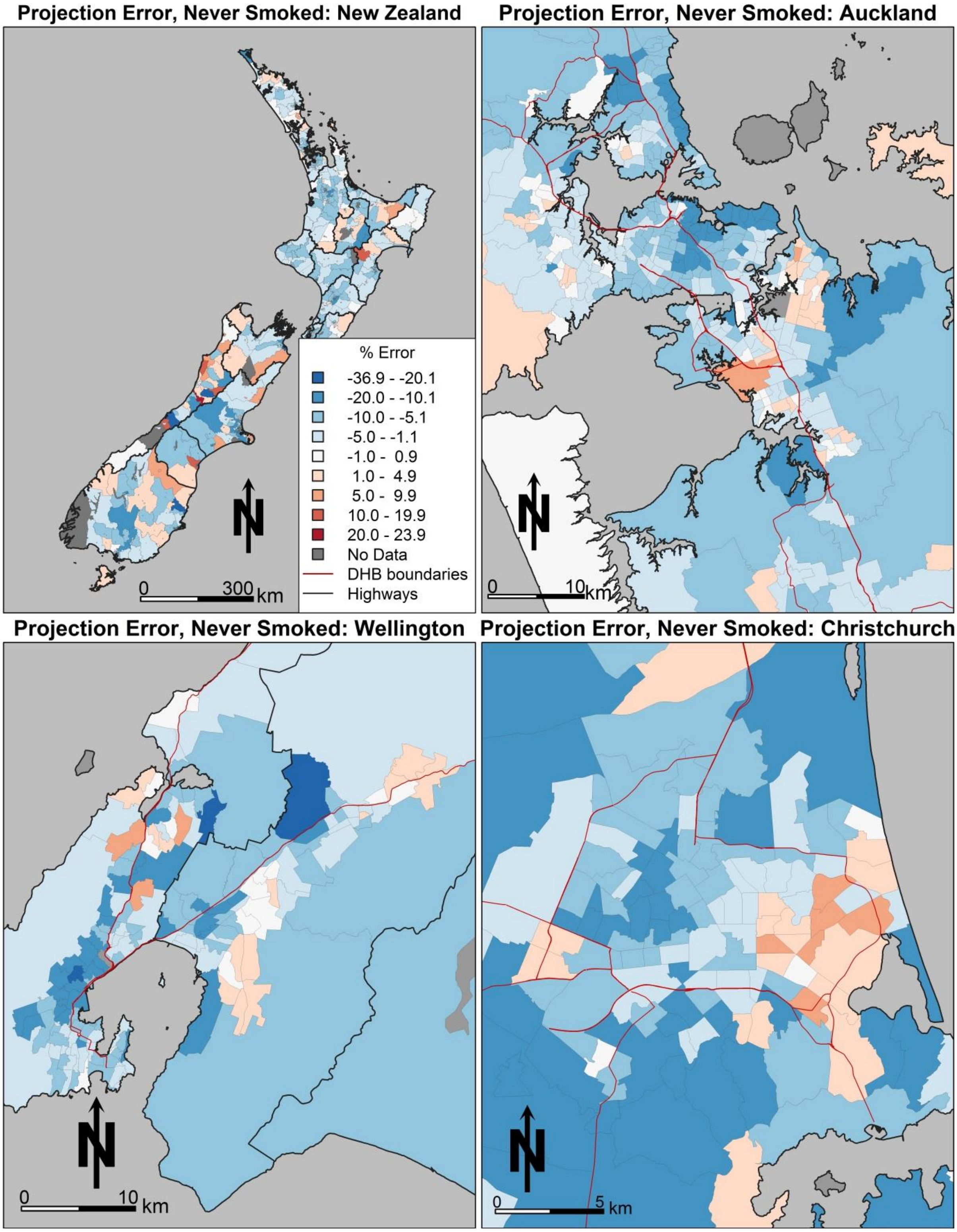


Figure 6.8: Errors for those who have Never Smoked in the Projected Validation model for 2013 based on 2006 Census data

Finally, the obesity estimates from the projected validation model can be compared to the NZHS obesity estimates at DHB level (see Table 6.5). The model provides estimates that are similar to the NZHS estimates and the standard 2013 model estimates, with the projected model providing estimates in 11 of 20 DHBs that are within 1 percentage point of the standard 2013 model output, and all except Auckland DHB within the NZHS 95% confidence interval. However, note that the national estimate falls slightly outside of the 95% confidence interval from NZHS data. Of the nine DHBs in which there was a discrepancy between the standard and validation models of greater than 1%, five were within 1% of the NZHS estimate (Canterbury, Lakes, Northland, Southern, and Tairawhiti). In some cases, differences between the standard model and the Validation model resulted in an improvement in the accuracy of the estimate (see Bay of Plenty, Lakes, Northland, Southern, South Canterbury, and Tairawhiti).

Table 6.5: Comparison of DHB level obesity rates for the Standard 2013 model and the Projected Validation model with the NZHS

	NZHS	NZHS 95% CI	Standard 2013 model	Projected Validation (2006-base)	Differ-ence (NZHS)	Differ-ence (Std 2013)
National	29.7	29.0–30.4	30.1	30.5	+0.8	+0.4
Auckland	21.8	19.7–24.0	25.6	26.3	+4.5	+0.7
Bay of Plenty	31.7	29.5–33.9	32.6	31.8	+0.1	-0.8
Canterbury	27.7	25.4–30.1	27.0	28.6	+0.9	+1.6
Capital and Coast	25.5	22.5–28.8	25.6	26.4	+0.9	+0.8
Counties Manukau	37.7	34.6–40.9	37.3	38.9	+1.2	+1.6
Hawke's Bay	33.8	30.8–37.0	33.3	32.4	-1.4	-0.9
Hutt Valley	31.0	28.0–34.1	31.2	31.7	+0.7	+0.5
Lakes	34.0	31.0–37.1	34.8	33.6	-0.4	-1.2
Mid Central	31.4	28.7–34.3	31.0	30.0	-1.4	-1.0
Nelson Marlborough	27.5	25.0–30.1	29.2	29.9	+2.4	+0.7
Northland	34.1	30.0–38.4	36.0	33.9	-0.2	-2.1
South Canterbury	33.1	28.9–37.5	31.2	32.0	-1.1	+0.8
Southern	29.4	26.7–32.3	27.6	28.6	-0.8	+1.0
Tairawhiti	37.3	33.1–41.7	38.9	36.9	-0.4	-2.0
Taranaki	31.5	28.8–34.2	30.3	30.3	-1.2	-0.0
Waikato	35.2	32.7–37.8	34.5	34.1	-1.1	-0.4
Wairarapa	32.1	27.2–37.5	31.3	30.9	-1.2	-0.4
Waitemata	24.3	21.9–26.8	25.0	26.4	+2.1	+1.4
West Coast	31.8	27.0–36.9	30.2	29.9	-1.9	-0.3
Whanganui	34.5	28.9–40.5	34.2	32.2	-2.3	-2.0

Overall, the Validation model is less accurate than the standard 2013 model, particularly when considering the external validation using smoking data. However, it is still well within accepted parameters for a SMSM. This indicates that this method performs well and provides a reasonable approximation of future obesity in an Aotearoa New Zealand context.

6.3.3 Projected models: Base, 2018, and 2023

Most of the results presented here will be compared to the Base model not to the Standard model, as the obesity estimates differ due to changes in the model construction (specifically the absence of deprivation from the projected models). Maps of estimated obesity rates for the Base, 2018 and 2023 models are similar to the standard model, though the base and projected estimates are generally slightly higher than standard estimates for a given CAU (Figure E.1, Figure E.2, and Figure E.3). Note that the Base model uses the same Census data as the standard model, the only difference is the absence of the deprivation variable.

The change in estimated obesity rates from the Base model (2013) to 2018 or 2023 are presented at DHB level in Table 6.6. None of these estimated changes are greater than 1%. Most DHBs have an estimated obesity rate for 2018 that is slightly below the 2013 projected estimate. The estimates for 2023 are in many cases slightly higher than for 2018, with the model suggesting a larger number of DHBs will show increases in obesity rates above 2013, though the majority still show a decrease compared with 2013. In particular, the model suggests a 0.5 percentage point increase in 2023 compared with 2013 for the high obesity DHBs Counties Manukau and Tairawhiti.

Table 6.6: Obesity estimates at DHB level for the NZHS and the three projected models, and projected percentage point change in obesity rates

		Projected estimates			Projected change*	
	NZHS	**Base**	**2018**	**2023**	**2018**	**2023**
National	29.7	30.8	30.5	30.7	-0.3	-0.1
Auckland	21.8	26.0	25.3	25.6	-0.7	-0.5
Bay of Plenty	31.7	32.7	32.3	32.4	-0.4	-0.3
Canterbury	27.7	28.9	28.6	28.7	-0.3	-0.1
Capital and Coast	25.5	26.4	26.1	26.1	-0.4	-0.4
Counties Manukau	37.7	38.7	38.5	39.1	-0.2	+0.5
Hawke's Bay	33.8	33.4	33.1	33.1	-0.3	-0.3
Hutt Valley	31.0	32.2	32.1	32.2	-0.1	-0.0
Lakes	34.0	34.6	34.4	34.4	-0.2	-0.2
Mid Central	31.4	30.8	30.7	30.8	-0.1	-0.0
Nelson Marlborough	27.5	30.3	30.1	30.1	-0.3	-0.3
Northland	34.1	35.0	34.8	34.9	-0.2	-0.1
South Canterbury	33.1	32.3	31.9	31.9	-0.4	-0.5
Southern	29.4	28.9	28.8	28.9	-0.1	-0.0
Tairawhiti	37.3	38.2	38.4	38.6	+0.2	+0.5
Taranaki	31.5	30.8	30.6	30.9	-0.1	+0.2
Waikato	35.2	35.2	34.4	34.3	-0.7	-0.8
Wairarapa	32.1	31.5	31.2	31.3	-0.3	-0.2
Waitemata	24.3	25.9	25.8	26.3	-0.2	+0.4
West Coast	31.8	30.3	30.3	30.4	-0.1	+0.0
Whanganui	34.5	33.0	33.2	33.3	+0.2	+0.3

*Compared with projected 2013 model.

Projected changes in obesity rates can also be examined at CAU level. Summary statistics (Table 6.7) show that roughly half of CAUs show a slight negative bias in the projected change in obesity rates (as both the mean and the median are negative). Additionally, the range of projected changes decreases slightly for the 2023 model, but these values exhibit a greater degree of spread from the mean (in particular the Standard Deviation values from Table 6.7 and additionally, Figure 6.9). Figure 6.9 shows very clearly that the majority of CAUs show projected changes within ±2%. This increased spread is not reflected in the mean and median values as the projected changes are approximately evenly spread on both sides of the mean.

Table 6.7: Summary statistics for obesity rates and the change in projected obesity from 2013 to 2018 or 2023

	Obesity rates			Change in obesity	
	Base	**2018**	**2023**	**2018**	**2023**
Minimum	16.11	15.47	14.76	-11.57	-9.89
Lower Quartile	28.56	28.26	28.33	-0.59	-0.66
Median	30.71	30.42	30.42	-0.25	-0.13
Mean	31.63	31.41	31.59	-0.22	-0.04
Spread	0.92	0.99	1.17	0.03	0.10
Upper Quartile	33.55	33.14	33.14	+0.09	0.42
Maximum	65.41	67.40	68.87	+11.25	10.53
Range	49.30	51.93	54.11	22.82	20.41
Std Deviation	6.28	6.47	6.58	0.97	1.29

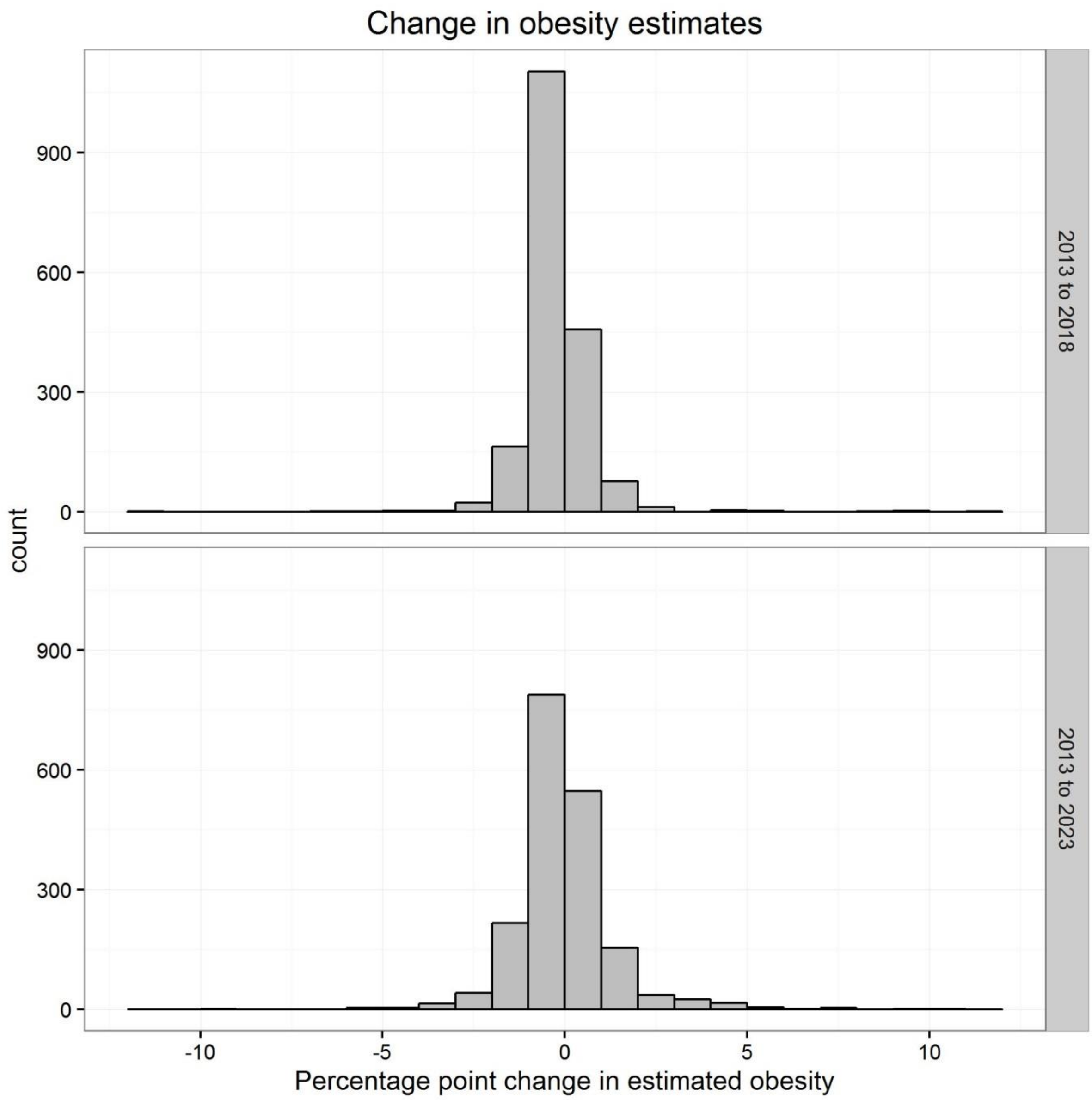


Figure 6.9: Distribution of changes in obesity estimates

Percentage point change data has also been mapped at CAU level (see Figure 6.10, Figure 6.11, and Figure 6.12). The categories for these maps are fixed so that the degree of change can easily be compared among different areas. Broadly speaking the projected models predict moderate increases in obesity in areas that currently exhibit high obesity rates, particularly Southern Auckland and East Cape. The model also predicts small to moderate increases in the currently very low obesity areas of Central Auckland and the North Shore for 2023. Decreases in obesity rates are predicted in the short term (2018) for Central and Western Auckland, and parts of the central North Island, but the comparison of 2018 and 2023 indicates that no further reductions in obesity rates are expected in these areas.

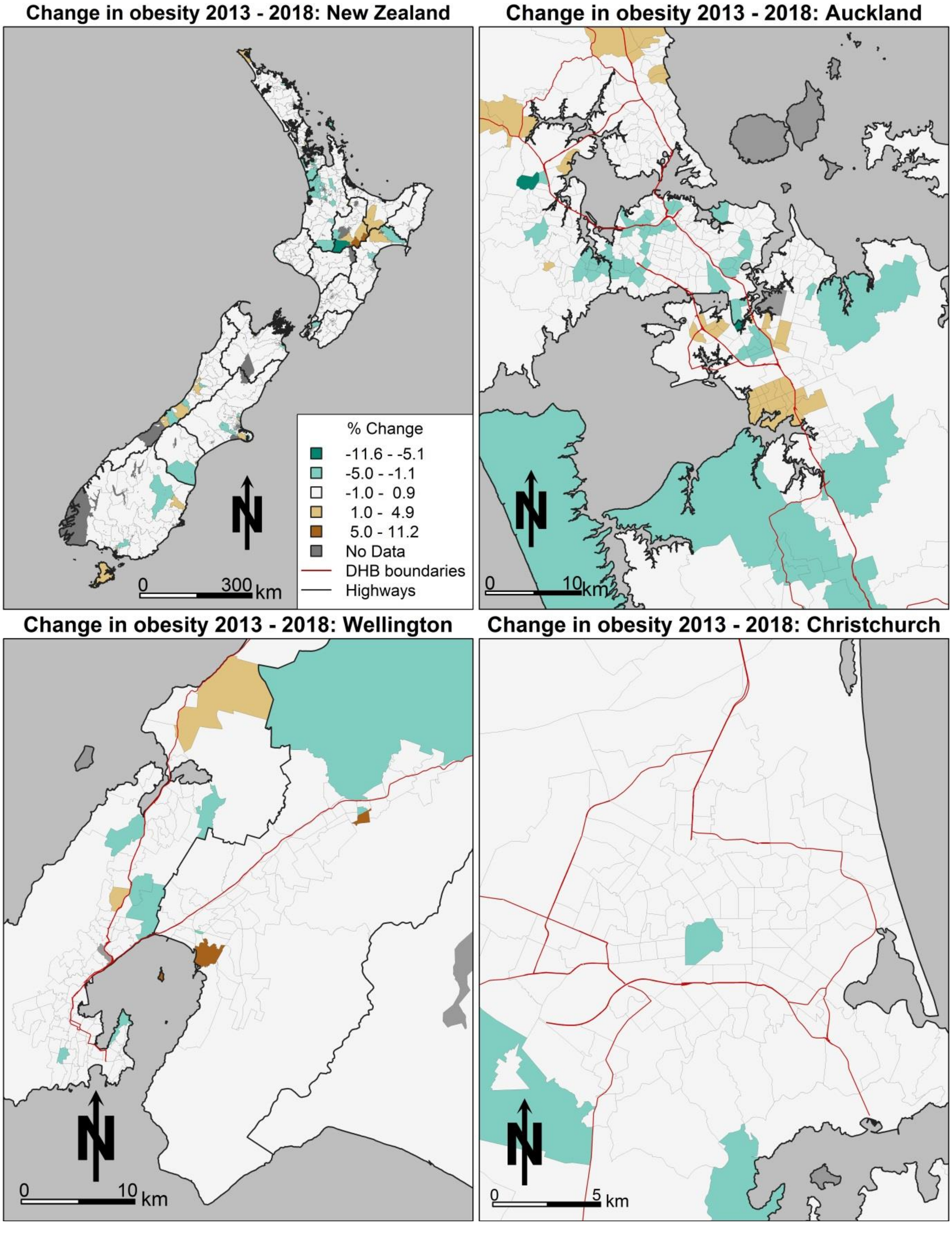


Figure 6.10: Percentage point change in obesity estimates for 2018 compared to 2013

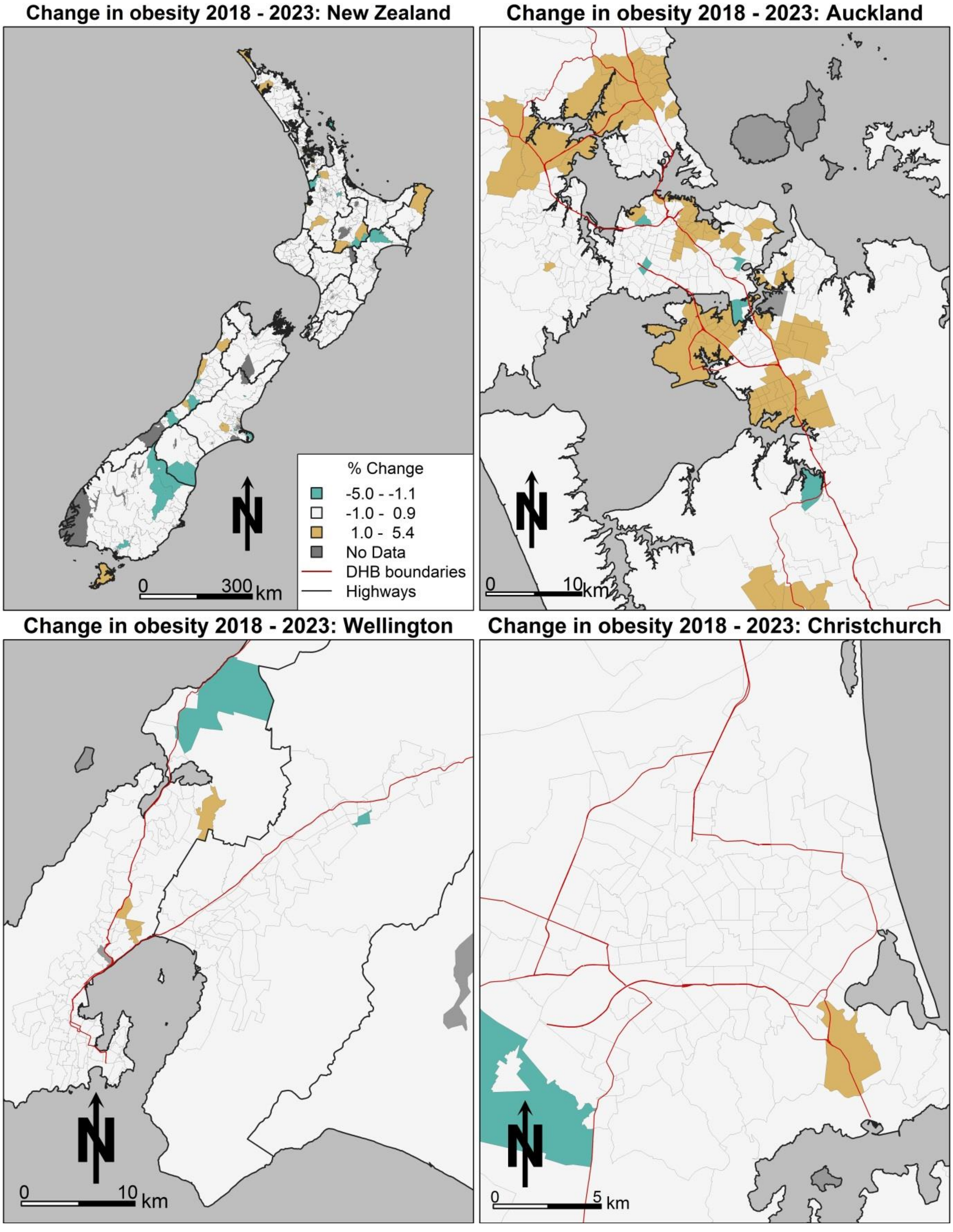


Figure 6.11: Percentage point change in obesity estimates for 2023 compared to 2018

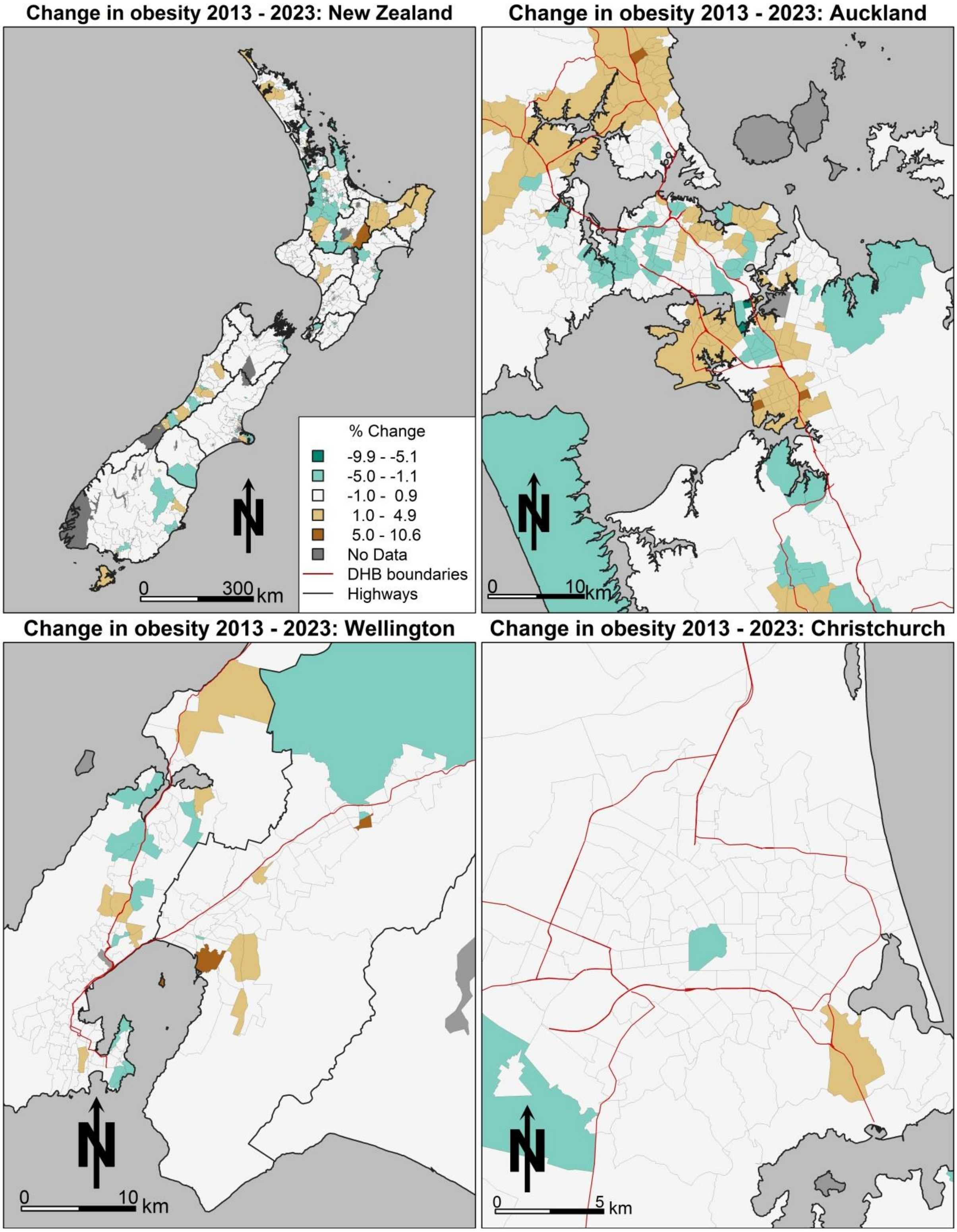


Figure 6.12: Percentage point change in obesity estimates for 2023 compared to 2013

6.4 Discussion of projection results

The previous section presented the results and validation of the projected version of SimAotearoa. This section will contextualise these results and discuss future possibilities of projected obesity models.

As with previous international studies (Ballas et al., 2005a; Dekkers, 2015; Vidyattama & Tanton, 2013), the static aging methodology was found to be a robust way to generate projected constraint tables, future obesity estimates, and a projected SMSM in Aotearoa New Zealand. External validation error was higher in the Validation model than for the Standard model (from Chapter 4), but well within the accepted margins for a SMSM. Adapting Vidyattama & Tanton's (2013) method for projecting the constraint tables to Aotearoa New Zealand's Total Response Ethnicity data posed some difficulty, as Aotearoa New Zealand ethnic groups do not sum to a single total (see Sub-section 4.2.3 for a discussion of Total Response Ethnicity). Despite this, the impact on the accuracy of the projected models appears to be minimal, with the absence of the deprivation variable having a much greater impact.

This section will cover three key topics. First, the limitations of the projection will be discussed (Sub-section 6.4.1). Second, the finding of increasing inequity will be discussed in greater detail than was possible in the results sections above (Sub-section 6.4.2). The final section will address potential future work related specifically to the projections (Sub-section 6.4.3).

6.4.1 Projection limitations

Important features of this model that must be considered when interpreting results include the absence of deprivation from the projected models, considerations of the accuracy of the projected constraint tables, the assumption that the current population is a reasonably proxy for future populations, the assumption that the relationship between the constraints and obesity rates remains constant over time, and importantly, that the future is never certain even with high quality data. Each of these factors and how they may affect the model will be discussed in this section.

The first issue to consider when assessing the accuracy of the projections is that the projected models do not contain deprivation as a constraint. Deprivation was an important part of the standard model from Chapter 4. The loss of deprivation as a constraint means that individuals are sometimes given a high weight in an area that contains individuals that are similar to them in terms of age, sex, ethnicity and labour status, but the area may be very unlike their home location in terms of deprivation. Because of this limitation, the predicted direction and magnitude of change are likely to be more accurate than the actual obesity estimates for any given area. The projected models fit less well than the standard model (Chapter 4), most likely due to the absence of deprivation among the constraints. The model still easily exceeds the accepted standards for a SMSM, but additional caution should be used when interpreting the obesity estimates generated by the model as the projections are less accurate than the standard model and the estimates produced by the validation model differed from the standard model. All projected models showed higher obesity rates relative to the standard model. The differing construction of these models is the likely cause of these differences.

The second key limitation is the assumption that the projected constraint tables are reasonably accurate. This assumption is mostly reasonable, but as demonstrated in Sub-section 6.2.2, the ERP tables show an unreasonable rate of population growth in the four months between the 2013 Census and the June 30 date used for projections and estimates, thus the precise estimated number of individuals in any group may be inaccurate. Consequently, it is important to exercise care with these results, they are unlikely to reflect the real future population exactly, but ideally should be relatively close.

Related to the second limitation is the method of projecting the LFS and ethnicity data for which there were additional considerations. The available labour force projection data are based on 2015 totals, not 2013. Given this variable had a relatively good performance when the validation model constraint tables were assessed, the impact of this on the simulation is likely to be minimal. In contrast, the ethnicity estimates are clearly too high due to the inability to sum total response ethnicity to a meaningful total. However, all four ethnic groups have been treated consistently and all are in proportion to each other. Thus, the impact on the results of the projection is likely to be no more than that of the LFS data.

The third limitation is that this model does not reflect any effects or potential effects of changes in health policy as it is based on the current, 2011-14 NZHS sample. This sample is assumed to be a reasonable proxy for the obesity status of New Zealanders in the near future and that the relationship between the constraints and obesity does not change over time, as discussed in Sub-section 6.1.4. This assumption is supported by recent estimates of obesity that have remained relatively consistent (Ministry of Health, 2012a, 2013b, 2014a, 2015a); there is evidence that the relationship between obesity and deprivation can change over time

(Ministry of Health, 2004b), and variation with other constraint variables is possible as well. However, it is not possible to tell if this will occur in the coming decade; keeping the projected simulations to relatively short time periods (maximum 10 years into the future) minimises the impact of this assumption being violated. The projected models apply the current state of obesity in Aotearoa New Zealand to the projected composition of future Aotearoa New Zealand (in terms of age, sex, ethnicity and LFS). As described earlier (Sub-section 6.1.4), the question this model is best able to answer is: what happens to obesity if nothing changes? This assumes that obesity in the Aotearoa New Zealand population has reached a stable equilibrium.

A fourth limitation relates to the increase in individuals with multiple ethnicities. As discussed in Sub-section 2.1.4, appropriate BMI thresholds are inconsistent among ethnic groups (Rush et al., 2009). Thus, it can be difficult to know how individuals with multiple ethnicities relate to the WHO BMI categories. If an individual identifies as Asian and Pacific, is their body structure more similar to Pacific Peoples where BMI overestimates body fat, or more similar to Asian ethnic groups, where BMI underestimates body fat? (Or somewhere in between?) This exposes one of the major criticisms of the use of the BMI index in assessing obesity in individuals — and one of the reasons why WHO BMI thresholds are used for everyone in the NZHS — every individual body is different (Deurenberg-Yap & Deurenberg, 2003; Evans & Colls, 2009; Rush et al., 2009). This difficulty is only magnified by the projected increase in multiple ethnicity.

6.4.2 Increasing inequity?

The projected models presented here show very little overall change in obesity rates compared to 2013. This may seem surprising given the degree of alarm raised in many quarters, particularly among public health professionals, about the 'obesity epidemic' (see Chapter 2), but is consistent with NZHS results between 2011 and 2014 which have hovered around 30% obese (Ministry of Health, 2012a, 2013b, 2014a, 2015a). The projected models exhibit only incremental change relative to the base model. From this it can be inferred that expected future demographic change will result in little overall change in obesity rates. Consequently, any changes that are observed in 2018 or 2023, once actual data are collected for these years, are likely to be due to changes in underlying obesity (i.e. obesity in the population was not at equilibrium at some point between 2013 and 2023).

The most notable change from the base 2013 model is a diverging trend in estimated obesity rates in some areas. Obesity rates in more deprived areas tended to increase (most notably in South Auckland and East Cape), and rates in less deprived areas tended to decrease (for example in central Wellington, the western part of central Auckland and Howick in eastern Auckland). This pattern, while common, is not universal. Relatively deprived West Auckland and Waikato, for example, showed decreasing obesity rates, whereas in some parts of less deprived central Auckland obesity rates increased.

It could be argued that the patterning of this divergence is a result of increasing Māori and Pacific populations raising obesity rates in some areas and increasing Asian populations decreasing it in others. However, some areas in which the projected models suggested decreasing or static obesity rates have high Māori and Pacific populations, such as West Auckland, and individuals in areas like this with static obesity are projected to have better health relative to a similar area with increasing projected obesity rates than if the same comparison was made with the static 2013 estimates from Chapter 5. Thus, this divergence suggests increasing obesity related health inequities. The burden of disease already falls disproportionately on those living in deprived areas in Aotearoa New Zealand; any change that further exacerbates this is of substantial concern (Chan et al., 2008; Ministry of Health, 2015a; Turley et al., 2006).

Increasing social and economic inequities will also likely contribute to widening health inequities, and inequity in obesity outcomes in particular. As discussed in Chapter 2, there is good evidence that low SES is strongly associated with higher levels of obesity, and that stress is a notable factor in this relationship (McLaren, 2007; Moore & Cunningham, 2012; Sobal & Stunkard, 1989). Increasing economic and social inequities are a widespread concern in New Zealand, and a focus of the new Labour Government; it remains to be seen whether this concern will deliver tangible change.

6.4.3 Future work with projections

A logical extension of the work in this chapter is to build a dynamic aging model. This type of model would be able to consider a much more complex range of variables when aging the synthetic population. Importantly, a dynamic aging model would be capable of evaluating current health status when predicting future health status. The additional computational requirements for a dynamic aging model (Dekkers, 2015) may not be advantageous when considering obesity on its own, as obesity appears to be at, or close to, equilibrium in the population. However, as discussed in Sub-section 2.1.5, obesity is merely the most obvious symptom of a much more serious suite of health conditions, for example NIDDM or CVD (World Health Organisation, 2000). A dynamic aging model may be preferable for modelling this type of important change in health status, where the current population may not be an adequate approximation of the future population (Dekkers, 2015).

One step that would improve the predictive qualities of the existing (static aging) projected models would be to find some way to incorporate deprivation into the model. Or at minimum, to restrict individuals in the microdata to area units that are ‘similar’ to their home location (see Sub-section 4.2.2). One possibility would be to try Ballas et al.’s (2005a) method of projecting constraint tables with the 2001, 2006 and 2013 deprivation scores.

With the 2018 Census approaching rapidly, there is the opportunity to make a ‘real world’ assessment of the accuracy of the model projection. Data suitable for verifying the accuracy of the 2018 projected model is likely to be available by early 2019, at which point the accuracy of some aspects of the model (except CAU obesity estimates) can be assessed. This is an excellent opportunity to assess the fit of the projected model more stringently than is possible with constraint table projections based on 2013 ERP.

6.5 Summary: The utility of projection

The purpose of this chapter was to address Objective 3: to develop a spatial microsimulation model (SimAotearoa) that estimates future adult obesity rates based on 2018 and 2023 population projections; and to test the validity of this model. Additionally, to address the projected portion of Objective 4: to explore the results of both static and projected spatial microsimulation models for obesity, diabetes, and key population subgroups, including how these results may be potentially relevant to policy. The projected models have been successfully built and presented here. Though these models are somewhat less accurate than the standard model (Chapter 4), they exceed the accepted accuracy standards (more than 80% of areas with less than 20% error) for a SMSM. Thus, these projected models can be considered to supply reasonable estimates of future changes in obesity in Aotearoa New Zealand.

As with all population projections, care is needed when using or interpreting the results of this model. Interpretation of these models should focus on direction (higher or lower) and magnitude of the predicted change in obesity rates, not the estimated rates themselves. The estimates of change in obesity rates are more likely to be accurate than the actual estimated rate of future obesity.

The results of the projected models presented here can be used in a similar manner to those in Chapter 4, though with a preference for the projected change in obesity, rather than the specific obesity estimates due to the limitations discussed above. These results are able to give policy makers an indication of expected patterns of change in obesity rates under a ‘no intervention’ scenario. The projected models are expected to be a useful tool when used as part of the process for planning future health services, particularly in combination with other information such as hospital admissions, and planning information.

Finally, the model suggests that little overall change in obesity rates can be expected based on population demographics. This is reasonable given that obesity rates have remained roughly consistent since the current sequence of the NZHS began in 2011 (Ministry of Health, 2012a, 2013b, 2014a, 2015a). One possible pattern in the results that is of concern is that obesity rates may continue to rise in the most deprived areas, while it decreases in the least deprived areas, causing widening health inequities. There is also the potential to evaluate model and policy performance once data from 2018 become available for study.

Chapter 7 General discussion

The preceding results chapters have presented the design (Chapter 4), validation (also Chapter 4), and results from both the static (Chapter 5) and projected (Chapter 6) versions of SimAotearoa. They have demonstrated that the model is both robust and useful for understanding obesity in Aotearoa New Zealand.

The purpose of this chapter is to draw the thesis results together and discuss them in the context of existing literature and ideas. Additionally, to address some of the broader concerns raised by the research that are out of scope for discussion within the results chapters. This chapter will address Objective 5: to evaluate and critique the outputs and potential uses of SimAotearoa. Note that concepts that are specific to a single results chapter have been discussed within the relevant chapter and will, generally, not be discussed here.

This chapter will have three main sections: addressing the model, its validation, and the limitations of the research (Section 7.1); examining and drawing into a broader context the intersection between social and spatial disadvantage (Section7.2) that was highlighted by the results in Chapter 5; and the policy implications of this research (Section 7.2).

7.1 Microsimulation, validation and limitations

As with any statistical model, SimAotearoa is an imperfect representation of the real world. Though care has been taken to select constraint variables that will predict obesity rates accurately and to validate the model carefully, it should not be interpreted as absolute 'truth'. Analyses based on the model are subject to this same limitation. In comparison, the 'standard' statistical approach using modelled survey data also has limitations, though with respect to the scale and complexity of analysis — most surveys are limited to analysis at a regional scale as discussed in Sub-section 2.4.1. The purpose of this section is to discuss the limitations of the work presented in this thesis.

A SMSM is only as strong as the data, methods, and validation that have gone into it. Thus, it is worth re-examining here the processes of model building and validation. This section will consider the modelling and validation methods used in SimAotearoa in a broader context than was possible in Chapter 4 and discuss some of the implications of the choices made earlier in the thesis. Sub-section 7.1.1 will cover the validation process, and sub-section 7.1.2 will cover the model construction. Sub-section 7.1.3 will cover limitations.

7.1.1 Validation

The purpose of validation is to check that the model represents the real world with a reasonable degree of accuracy. As such, validation is an important component of any SMSM (Edwards et al., 2011). The validation methods used to build SimAotearoa included both internal and external validation methods. To briefly re-summarise these for the reader: internal validation methods involve essentially checking the simulated model against its inputs to ensure that it is an accurate representation of the data used to build it. As discussed in Sub-sections 4.1.2 and 4.1.3, the strictest definition of external validation requires comparing the simulated results to a separate data set not used in the SMSM. However, an alternative definition of external validation requires comparison to an unconstrained variable — one that was not used to build the model. The small area Census smoking data used to validate SimAotearoa meets this second definition of external validation.

Different validation methods produce different results. Indeed, this can be seen in the differing results produced by the three levels of the smoking variable in the external validation. The main validation methods used here, TAE and SAE, are widely used for different types of SMSM in the literature (Anderson, 2013; Koh et al., 2015; Lovelace & Ballas, 2013; Smith et al., 2009).

Internal validation methods primarily involved comparing summaries of simulated small area constraint data with Census data, in order to check that model outputs resembled the input Census data. Methods that could have been used for internal validation but were not, included plotting relationships between modelled and Census data for each category of all the constraint variables at small area level (Edwards & Clarke, 2013), or calculating a regression model and R^2 for these relationships (Edwards et al., 2011). Alternatively, these data can be aggregated to a larger scale and compared to constraint variables at this level (Edwards & Clarke, 2009).

External validation is generally considered more rigorous than internal validation. Accurately estimating a variable that was not constrained in the simulation is more difficult and requires a higher degree of accuracy from the model (Edwards & Clarke, 2009). External validation methods used for SimAotearoa included comparing DHB and national level estimates of obesity between the simulation and estimates using standard methodology, summaries of the TAE compared to smoking data, as well as plots of simulated vs Census smokers, and maps of the SAE validation error.

The external validation of SimAotearoa described above was relatively rigorous, in comparison to some published studies. One of the most rigorous published examples of external validation comes from Edwards et al. (2011) and uses data from a completely unrelated data set, obesity-linked cancers in this case. It is worth noting that Edwards' methodology is much more rigorous than most other obesity models have used. For example Koh et al. (2015) and Edwards and Clarke (2009) rely solely on internal validation, and Cataife (2014) uses primarily internal validation, with only a city-wide external comparison to other another data set.

SimAotearoa used smoking data from the Census as an external validation variable. This was an unconstrained variable in the validation analysis, however it does come from the same data set used to build the model (the New Zealand Census). Consequently, the smoking data set is subject to the same Census data related limitations as the data used to build the model, primarily the random rounding used in the Census, plus any bias arising from the Census undercount (Statistics New Zealand, 2013a, 2013b). An additional possible source of error is the 5% (approximately) of Census respondents refused to answer the smoking question in the Census. Although some NZHS respondents also refused to answer this question, the number who did so was too small to model this as a separate category, as discussed in Sub-section 4.3.3.

The main alternative external validation data set considered was the VDR, which is interpolated from transactional data and, from the perspective of validating a SMSM, contained many spatial inconsistencies. Thus, the VDR was not used for validation. Smoking data might be considered an unusual choice for validating an obesity model as the relationship between smoking and obesity is complex (Klesges et al., 1989). However, both are predicted with the same variables, which allows the use of smoking as a validation variable in this case. The purpose of external validation is to test how well the model predicts an unrelated variable for which data are available; usually this would be a variable which is related to the primary variable of interest (obesity). However, the key concern is to test whether the variable combination is able to predict real world health data with reasonable accuracy, so a variable predicted with the same set of constraints should be an acceptable substitute. In future it may be possible to obtain updated VDR data, cancer data, or data from the “B4 School” checks (for children) from the integrated data infrastructure (IDI) for validation purposes (Stats NZ, 2017a).

Against this background, it can be seen that the validation of SimAotearoa was superior to all but the most rigorous standards applied to similar published models. And additionally, that SimAotearoa provided a high degree of accuracy compared to similar models (Cataife, 2014; Edwards et al., 2011; Koh et al., 2015; Smith et al., 2011).

7.1.2 Model construction

Selecting the correct survey microdata is important to the output of the model, particularly when the model is intended to cover a wide area with differing population composition among constituent sub-areas. The results of SimAotearoa demonstrate that a single microdata set cannot be used with impunity across areas of differing composition. The use of different subsets of the microdata for different areas in the model was a key difference between SimAotearoa and other similar SMSMs. The fit of the model at DHB level was acceptable for most DHBs without the restriction of microdata, but was noticeably poor in several key DHBs including the three Auckland DHBs: Auckland, Counties Manukau, and Waitemata. Regardless of which variables were used to build the model, or which optimisations were tested, only restricting the microdata improved the estimates in these areas. This is an important point for future SMSMs, both in Aotearoa New Zealand and any internationally that cover a wide area containing diverse populations.

The importance of the microdata sample to the SMSM also suggests that the composition of the population in an area is a key determinant of local obesity rates. This contrasts with the obesogenic environment paradigm (Egger & Swinburn, 1997), as it suggests — but cannot confirm — that the characteristics of individuals living in an area may be more important than the environment in which the live as a predictor of their obesity status. This is not to say that the environment has no impact in the individual, but rather that environmental impacts on obesity may be smaller than individual risk factors. This would suggest that the most beneficial changes to the environment may come from large scale structural changes that may improve the individual-level determinants of obesity and promote behavioural change. Examples might include actions to reduce inequity, or tax changes that encourage the consumption of fresh fruit and vegetables or discourage sweetened, highly processed foods and beverages, as will be discussed in Section 7.2 below. The impossibility of confirming this from the SimAotearoa results cannot be over stated, nevertheless, it is an avenue that may be worth further investigation.

Future improvements to the model may also alter the results. The benefit of microdata restriction was discovered late in the model building process, and thus has not been tested in combination with other methods to improve the quality of the simulation outputs. In particular the model may benefit from repeating the variable selection process and modelling with *k*-means (Smith et al., 2009) within a restricted data paradigm. Alternatively, collecting a sufficiently large NZHS sample across multiple years to restrict all microdata to their home DHB within the SMSM may also be of benefit.

7.1.3 Limitations

The interaction between Māori and Pacific Peoples, deprivation, and obesity cannot be overlooked as a source of confounding error. Māori and Pacific Peoples are greatly overrepresented among those living in deprived areas, and it is impossible to disentangle the effects of ethnic differences in body composition from the effects of deprivation in these areas. It is likely, then, that obesity in deprived areas has been somewhat overestimated. But, the inability to disentangle these three (obesity, deprivation, and ethnicity) is also a limitation of the model as it promotes thinking about a very complex situation in a simplistic and one-dimensional way.

Because SimAotearoa is a complex statistical model, it cannot account for individual experiences of obesity in Aotearoa New Zealand. As discussed in Sub-section 5.3.1, SimAotearoa makes assumptions about the socio-demographic profile likely to be associated with obesity. This means that actual obesity rates in a specific area may vary from those expected based on the composition of the area. Moon et al. (2007) make a similar point in relation to a different methodology also used to generate small area estimates of obesity.

A related point is the way in which the model and its results condense a complex situation to a simplistic and one dimensional metric, and display it on a map; thus presenting it as an objective truth (Harley, 1989). It is critical that the results presented in this thesis are not simply used as another means to stigmatise already marginalised communities (Cochrane, Corbett, Evans, & Gill, 2016). To some extent, that is the purpose of later sections of this discussion (see Section 7.2), but further research is required to fill out gaps that have been highlighted by some of the results (see Sections 8.3, 8.4, and Chapter 6).

SimAotearoa has two key omissions: the exclusion of children from the model, and the lack of dynamic aging in the model. Both of these were out of scope for the project, but the absence of children in the model presents a larger problem. Obesity in children is of considerably greater concern from a Public Health perspective; there is much more opportunity to prevent obesity than to cure it as sustained long-term weight-loss in individuals is difficult to achieve (Aphramor, 2010). Incorporating children and households into the model is a major avenue for future research (addressed in Section 8.3). Dynamic aging is another possible avenue of future research, as this would enable the assessment of different scenarios of future population change.

BMI is widely acknowledged as an imperfect tool for the measurement of obesity (Deurenberg-Yap & Deurenberg, 2003; Evans & Colls, 2009; Gallagher et al., 1996; Rush et al., 2009), but it is an excellent tool for population surveillance due to its wide use and simplicity of measurement (Ministry of Health, 2008a; WHO Expert Consultation, 2004). A higher BMI is associated with presence of metabolic syndrome (an early indicator of NIDDM and other health issues), but some obese people are metabolically normal, while some normal weight people exhibit metabolic syndrome (Ervin, 2009; Grant et al., 2008). The importance and benefits provided by the results, and particularly their comparability to other work, must be weighed against the potential for errors and inaccuracies introduced by the use of BMI as an indicator of obesity in this study. The NZHS uses BMI as the primary indicator of obesity (Ministry of Health, 2008a), thus BMI was used primarily in this thesis for comparability reasons as discussed in Sub-section 2.1.4. One way to mitigate the issue of BMI would be to use data that examined the underlying health issue (e.g. metabolic syndrome), blood samples have been taken for some NZHS years, but those data were not available for this analysis. BMI and waist measurement provided very similar results, though waist measurements estimated a narrower range of obesity prevalence than did BMI.

The quality of the model results is dependent on the quality of the data. The static SMSM and its validation (Chapter 4 and Chapter 5) used high quality, official data sources (Census and NZHS). For Chapter 6, however, some of the constraint tables needed to be projected and the data quality here is necessarily lower as discussed in Sub-section 6.3.1. The quality of the projected model in Chapter 6 was also constrained by the lack of deprivation as a variable available for use in that model. It is worth noting that the NZHS sampling frame includes only occupied private dwellings, thus if there are any biases in the occupants of non-private dwellings (e.g. prisons, student hostels), there will also be a bias in the sample and potentially the model. New Zealand Census data is randomly rounded to base three, which caused errors in the initial models; to offset this, all constraint tables were standardised to a single set of totals (see Sub-section 4.2.1).

The size of the areal unit also plays a role in the accuracy and specificity of the results. The areal unit available for use in these analyses (CAUs) was slightly too large for SMSM, as the population became somewhat homogenised at this scale. This is discussed in greater detail in Sub-section 4.4.1, but it affected all of the SimAotearoa results in Chapter 4, Chapter 5, and Chapter 6. Statistics New Zealand has proposed changes to the Census output areas which may offer comparable data at finer spatial scales for future SMSM projects in Aotearoa New Zealand.

The synthetic population and the estimates for obesity produced by SimAotearoa are based on the composition of the population in the area. Thus the model cannot account for any environmental differences, such as the walkability of an area or the local price of healthy food, a limitation acknowledged in other similar work (Cataife, 2014). These environmental concerns may be at neighbourhood scale (walkability of the area), regional scale (price of food), or a mix of the two. There is an argument for combining the SimAotearoa output with these environmental factors in a multi-level model to better account for and assess this variation.

7.2 At the intersection of spatial and social disadvantage

The previous section discussed some of the technical aspects of the SMSM methodology and SimAotearoa, including its limitations. One of the findings that has been highlighted (see Sub-section 7.1.3 and Sub-section 5.3.3) was that there is a strong spatial variation in obesity outcomes resulting from the interaction between SES, ethnicity, and obesity in Aotearoa New Zealand. The purpose of this section is to discuss these interactions in greater detail.

Combined, low SES, ethnicity, and obesity contribute to particularly strong social and health-related disadvantages. Further, there are obvious inequities evident in the spatial variation of obesity rates, which can differ greatly even among neighbouring areas. It would be naïve to assume that these determinants act independently of each other, particularly given their spatial congruence. It is not sufficient to detect this health inequity and then make no attempt to understand or explore it; however, in exploring the health inequities associated with the intersections between obesity, ethnicity, and social deprivation, this section will depart substantially from the rest of the thesis.

Instead, section will cover four main topics relating to the societal implications of this thesis: the stigma of obesity (Sub-section 7.2.1), the impact of inequities (Sub-section 7.2.2), the importance of place (Sub-section 7.2.3), and ideal theory — a framework for utilising ideas of social justice in public health (Sub-section 7.2.4). Underlying this is a commitment to acknowledge that although mathematical simulations can offer valuable insights, analyses such as this must also consider the essential social justice concerns of health geography (Rosenberg, 2014).

Intersectionality is a theoretical framework that describes how different aspects of social disadvantage interact. Different types of disadvantage produce overlapping systems that accentuate each other, and contribute to different experiences of discrimination (Davis, 2008). For example, it is well known that individuals with low SES have poorer health outcomes, as do individuals of minority ethnicity, but these two factors also interact (Krieger, 2000). An individual of both low-SES and minority ethnicity will likely have worse health outcomes than someone of low-SES and the majority ethnicity, *and* worse health outcomes than an individual of the same ethnicity but higher SES. These differences have often been attributed to biological or cultural differences between groups[37] − in statistical terms, they are treated as a covariate requiring control and mitigation rather than a variable of interest — though this approach has been criticised (Mullings & Shchulz, 2006). These disadvantages are also imbued in *places*, both because individuals may collect into localised areas as well as through social attitudes towards those places (Keene & Padilla, 2014). The following section explores the aforementioned nexus of social and spatial intersections among SES, ethnicity, and obesity, and concludes with a theoretical frame work that may assist in turning knowledge of inequities into useful policy interventions.

7.2.1 Out of sight: Stigma and othering

A person who is obese is likely to be perceived to be lazy, stupid and worthless, even by health professionals (e.g. Fontana, Furtado, Mazzardo, Hong, & de Campos, 2016; LeBesco,

[37] This is particularly awkward when there are real biological differences in body composition between ethnicities that promote overestimation of obesity in Māori and Pacific Peoples, and thereby accentuate socio-economic differences (see Section 2.1.4).

2011; Puhl & Brownell, 2001; Puhl & Heuer, 2009; Schwartz et al., 2003; Tomiyama et al., 2015). These negative connotations construct the fat body as ‘Other’, as well as risky, amoral, and undesirable (Evans, 2006; Johnson et al., 2004; LeBesco, 2011; van Amsterdam, 2013). It is thus unsurprising that obesity is highly stigmatised, and that the stigma of obesity can be difficult to overcome, even for individuals with high SES (King et al., 2014). This stigma and the resulting discrimination can have an array of harmful effects on individuals, some subtle and others less so, including economic, health — beyond any direct effects from excess body fat, education, and interpersonal relationships (Puhl & Brownell, 2001; Puhl & Heuer, 2009; Schafer & Ferraro, 2011).

As discussed above, obesity in Aotearoa New Zealand is concentrated into spatially confined areas with lower socio-economic status, thus making it ‘out of sight, out of mind’ for most of what has been termed ‘middle New Zealand’[38]. The contact hypothesis suggests that positive social contact between groups is one of the most effective ways to reduce discrimination among people of different ethnicities, and this also applies to obesity (Alperin, Hornsey, Hayward, Diedrichs, & Barlow, 2014). Those living in low obesity areas may be assumed to have less contact with obese individuals than those living in areas with higher obesity, particularly in cases like central Auckland which is relatively homogenous (Bolt, Burgers, & Van Kempen, 1998). This lack of contact is likely to exacerbate discrimination and stigmatisation on a population level, as is negative contact on an interpersonal scale (Alperin et al., 2014).

The moral judgements surrounding obesity open up strong intersections, particularly with groups that are already marked as deviant compared to the euro-centric middle-class ‘norm’ (van Amsterdam, 2013). This is exacerbated by a tendency to ignore or minimise the impacts of intersecting identities such as SES or ethnicity when discussing obesity from a medical or public health perspective (Evans et al., 2008). The decision to use only the WHO obesity cut offs and not ethnicity specific cut offs — for the NZHS and in this thesis — is an excellent example of a structural inequity contributing to further stigmatisation. Though this decision has an excellent statistical rationale, it does not have an objective effect on the interpretation

[38] ‘Middle New Zealand’ is a term favoured by several recent Prime Ministers to describe ‘average’ New Zealanders as a group. It can be inferred to describe predominantly Pākehā/New Zealand European, middle to upper-middle class families living in their own home.

of the resulting data due to the higher obesity rates it produces for Māori and Pacific Peoples (see Sub-section 2.1.4).

7.2.2 Inequities to outcomes

Though reducing the stigma of obesity is important, so too is addressing the health inequities associated with it. The very strong association between SES and obesity suggests that a large proportion of the ‘obesity epidemic’ in Aotearoa New Zealand has arisen from increasing inequity over recent decades that disproportionately affects members of lower socio-economic groups. Since the early 1990s, social and economic policy has increasingly marginalised those on the lower end of the socio-economic spectrum, which in turn disproportionately affects Māori and Pacific Peoples (Howden-Chapman, 2015). Consequently, a greater burden of health disparities in general, and obesity in this specific example, falls on Māori and Pacific Peoples. Regardless of whether obesity causes ill-health (the fat acceptance movement contends that it does not (Kwan, 2009)), this intersecting inequity — socio-economic status, with ethnicity, with obesity — must be addressed when considering health interventions.

Obesity cannot be disentangled from ethnicity, partially because structural inequity and low SES in Aotearoa New Zealand cannot be disentangled either. Experiencing racial discrimination is negatively associated with a broad range health outcomes (Harris et al., 2012; Harris et al., 2006b). This can be exacerbated by health care and research that is insensitive to the needs of Māori (Warbrick et al., 2016). Although there is no evidence that racial discrimination is associated specifically with obesity in Aotearoa New Zealand (Harris et al., 2012), there is some evidence in the USA that it does contribute to increased BMI (Gee, Ro, Gavin, & Takeuchi, 2008). Living in an area with many similar people can have benefits (Bolt et al., 1998). For example Māori who lived in an area with high Māori population density experienced a protective general health effect, though again there is no evidence with respect to obesity (Bécares et al., 2013).

Other aspects of social inequity may also have subtle effects on wellbeing, which can include higher rates of obesity. For example, elevated obesity rates have been found amongst lesbian, gay and bisexual[39] youth in the USA across multiple ethnicities, though the effect may be

[39] These studies did not consider transgender youth or other gender or sexuality minority groups.

dependent on gender (Austin et al., 2013; Austin et al., 2009). Another example is the way in which low SES and gender interact to alter obesity risk through gendered norms around providing and caring for children. Evidence suggests that mothers -- particularly solo mothers -- in food insecure households in the USA may have a higher risk of obesity than do fathers in the same position (Martin & Lippert, 2012).

Housing is a key foundation of society. Insecure or poor quality housing has significant flow on effects including health, welfare, social systems, and employment, and is strongly associated with low SES and inequity in Aotearoa New Zealand (Howden-Chapman, 2015). Housing costs are a key driver of inequity in Aotearoa New Zealand, due to a high proportion of income spent on rent in lower-income households relative to those with higher income leaving limited funds available for other items such as heating costs or food (Howden-Chapman, 2015; Perry, 2017). Food insecurity, where a household has an insufficient or inconsistent supply of food, is associated with obesity (Dietz, 1995; Martin & Ferris, 2007; Rush et al., 2007). Food security is a complex issue (see Sub-section 2.3.4), but this curious paradox is likely linked to the inexpensiveness of high-calorie, nutrient dense foods relative to higher quality ‘healthy’ foods (Rush et al., 2007).

As illustrated above, examining broader socio-spatial phenomena can help elucidate how forms of disadvantage with no apparent connection to the determinants of obesity still have an impact on body weight and obesity. The most likely pathway through which discrimination − and other forms of disadvantage − acts on body weight is stress (Moore & Cunningham, 2012). Chapter 2 established a link between stress and obesity (see Sub-section 2.2.2), and there is also a well-established link between minority groups and stress (Meyer, 2003). Again, this does not necessarily translate into an observable increase in obesity rates (Harris et al., 2012). However, this does suggest that focusing solely on energy balance (see Sub-section 2.2.1) will fail to address some of the underlying causes of obesity.

7.2.3 Place matters

One of the key findings of this thesis has been the spatial clustering of obesity — alongside deprivation and minority ethnicity — into a small subset of areas. The heterogeneity of obesity estimates and substantial spatial segregation between areas of high and low obesity represents a significant spatial health inequity, particularly in Auckland (see Sub-section 5.3.3). This illustrates how much more obesity affects low income communities — areas that also experience inequities on other axes. Together, this compounds the effects of stigmatisation and disadvantage within small geographic areas.

Both individual and neighbourhood level SES are known to have an impact on health. For example, Gaskin et al. (2014) found that ethnicity as well as both individual and area based measures of social deprivation had an influence on diabetes prevalence in the USA. Whether these impacts arise from features of the local area, or the composition of the population can be difficult to disentangle (Diez-Roux, 1998). Further, the relationship between obesity and deprivation is strong, but it is mediated by other factors such as age and ethnicity. There are areas of low SES that have low obesity rates due to ethnic composition and age profile of the population (see Sub-section 5.2.2). Caution is required however, even MBs which are much smaller than the CAUs used in this analysis, are unable to fully capture the heterogeneity and experience of deprivation at an individual level in the population (Salmond & Crampton, 2002).

For practical reasons, such as housing affordability, people of low SES can sometimes cluster together in socially deprived areas. This clustering can have both positive and negative impacts (Bolt et al., 1998). Low SES individuals are often the last to be considered despite most often having a higher need for assistance. Emergency and aid responses to the Christchurch Earthquakes are evidence of what has is often referred to as the ‘Inverse Care Law’ (Howden-Chapman et al., 2014). This vulnerability can expose this group to increased stress, which is associated with increased risk of obesity and other negative health outcomes (see Sub-section 2.2.2). Conversely, the concentration of similar social groups can provide an increased sense of community in some circumstances (Bolt et al., 1998), and some communities can be resilient — and healthy — despite high levels of social deprivation (Pearson, Pearce, & Kingham, 2012).

Stigma and disadvantage may also be attached to places rather than individuals. Keene and Padilla (2014) considered how places might impact on health inequities independent of other axes of social difference; a phenomenon they called spatial stigma. Spatial stigma is argued to impact on health through three pathways: access to resources; stress and coping, including interpersonal discrimination; and identity formation and management, including social isolation and othering of neighbours. Additionally, there is some evidence from the UK that spatially clustered disadvantage may confer negative effects on local residents, though the mechanics of this are complex and inconsistent (Buck & Gordon, 2004).

Through these examples, it appears that places can have an effect on health that is greater than the sum of the contextual and compositional attributes that are present in that place. Place-based effects on health may in many cases be an expression of other forms of privilege or disadvantage. However, it is also apparent from the results of SimAotearoa that places can also bring together different kinds of disadvantage in one location. On a population level, the intersections of factors such as ethnicity, deprivation, and obesity are also inherently spatial intersections; and these intersections will be influenced by the composition of the population, and the environmental context of each place. Thus, even where conditions appear similar, the effects may not be. The results presented in this thesis are best considered as an enhancement to existing data and decision making, not a replacement. In particular, it is important to remember that individual level outcomes can be very different to those observed at any aggregated scale (Macintyre, Ellaway, & Cummins, 2002; Robinson, 1950).

7.2.4 Finding a way forward: Ideal versus non-ideal theory

Rosenberg (2014) argues that it is insufficient to merely identify an inequity, say ‘we must fix this’, and assume that things will get better as a result. Instead, Rosenberg (2014) proposes a theoretical framework using idealist theory, based on Valentini (2012) and Rawls (1999), to identify both the ‘ideal’ aspects of a public health system and the realistic and practical compromises that may actually work. Ideal versus non-ideal theory[40] is broken down into three components: full versus partial compliance theory, utopian versus realistic theory, and end-state versus transitional theory; these will be explained in greater detail below. This sub-section will consider how ideal/non-ideal theory might apply to obesity in Aotearoa New Zealand, and how this relates to the results of SimAotearoa. In particular, the focus will be on how ideal/non-ideal theory may help inform policy changes that can be made from within the health sector.

Full compliance versus partial compliance theory examines what obligations apply, either to individuals or to officials, in circumstances where these obligations are either fully met or only partially met (Valentini, 2012). Full compliance theory might suggest that public health professionals are obligated to ensure that there are no spatial or social differences in the prevalence of obesity in Aotearoa New Zealand, nor in the care provided.

[40] These pairs of theories are presented this manner (one versus the other) in the original reference.

Partial compliance is substantially more common, so the key question is: "what ought we to do in circumstances where others do not do their part?" (Valentini, 2012, p. 655). A partial compliance theory position might suggest that no health care system is capable of achieving absolute equality of outcomes across several major health determinants at any spatial scale. It should be noted that central government can require compliance from individuals through legislation, though it may not be politically expedient to action some changes at a national level. In such a case, the responsibility then falls to regional public health services and local government.

While both the full- and partial-compliance scenarios are interesting on their own, when examined side-by-side, the two theories allow the desirable but often impractical 'ideal' scenario to be tempered against the more realistic 'non-ideal' scenario to identify a plausible but aspirational middle ground. In the case of full compliance versus partial compliance theory, this would suggest that a focus on reducing inequities in obesity prevalence and treatment provision, as well as facilitating weight loss in the most obese areas should be a priority. Such actions might weaken the interrelationship and spatial intersections between low SES, ethnicity, and obesity, thus reducing health inequities. SimAotearoa can facilitate the identification of high obesity areas for high priority interventions, as well as areas where intersections between obesity and other key forms of discrimination may be common (e.g. areas with high rates of obesity and high percentages of minority ethnicities). An example might be using the highest obesity quintile from one of the maps in Sub-section 5.2.2 or 5.2.4, potentially combining this with other data. In these areas, additional training for practitioners to reduce structural inequities may be beneficial (see the discussion in Sub-section 7.3.2).

Utopian or idealistic theory versus (more or less) realistic theory considers whether or not the practical constraints of implementing change in a world with limited resources should constrain theorising about what is just, and if so which constraints should matter (Valentini, 2012). Utopian or idealistic theory might suggest that there should be no barriers to accessing anti-obesity health care, including removing barriers such as the spatial, financial, and time aspects of access, discrimination, and physical or equipment limitations across all levels of care.

Using realistic theory, the key aspects of care can be interrogated. Example questions might include: what aspects of these barriers are most important? Which can realistically be provided or improved? And where are they most needed? When contrasted, this pair helps to identify key barriers — and intersections between these barriers — and then find practical ways to combat them. SimAotearoa can facilitate this by providing obesity estimates (main obesity outputs in Sub-section 5.2.2) for access calculations using other tools, such as an origin-destination matrix, and identifying high priority areas, for example using a map like the one identifying populations of 'at risk' youth in Sub-section 5.2.4.

End-state versus transitional theory considers what the long-term goals are to achieve an optimum state, or whether the focus should be on small improvements without considering what the system should look like when transformation is complete (Valentini, 2012). End-state theory might suggest a system where a specified set of anti-obesity services are readily available (perhaps in a primary care setting) in all areas with a high obesity rate, and that these services are provided in a sensitive and appropriate manner.

From a transitional theory perspective, any change which makes anti-obesity services more accessible, or removes barriers to their use contributes to making the system more equitable, even if there is no consensus about what the system should eventually look like. An alternative application of end-state theory might describe a situation where many of the environmental determinants of obesity have been addressed or optimised (e.g. a reduction in the consumption of unhealthy food and sugary drinks, commute times reduced and more active travel modes dominant, living wages, shift work reduced etc.) and obesity rates are falling. Similarly, transitional theory would suggest that any change which helps to address one or more of these environmental determinants is a positive change, even if the change does not go as far as public health professionals would prefer.

When contrasted, end-state and transitional theory help to visualise what the health system could look like, as well as intermediary steps to achieve positive change. SimAotearoa can facilitate this through identifying areas with high rates of obesity using the main obesity outputs in Sub-section 5.2.2, either for providing services or for targeted environmental improvements based on other analyses.

This sub-section has illustrated how ideal/non-ideal theory can be used to identify important public health outcomes, assess these against what can realistically be achieved, and select a middle ground that is both practical and aspirational. This is a tool that may be useful for policy development. This section has also illustrated that the outputs of SimAotearoa are useful in providing key data for decision making processes to achieve these goals. From this perspective, SimAotearoa is more useful as a data input and decision support tool than it is for suggesting specific policy settings.

7.3 Policy implications

The previous section discussed the interaction between low SES, ethnicity, and obesity. This final substantive section of the discussion turns to the question of how SimAotearoa could be used for policy purposes.

As discussed above, obesity is a problem with a high level of complexity and interrelatedness. Many of the underlying conditions that contribute to the high levels of obesity in Aotearoa New Zealand are outside of the health sector's sphere of influence. Many health policy initiatives attempt to influence individual behaviour in the hope of preventing obesity, despite the overwhelming dominance of the environment as a driving force behind increasing obesity rates (Egger & Swinburn, 1997). Figure 7.1 illustrates this disjoint between health policy and obesity outcomes. Consequently, tackling obesity from a policy perspective can be a very difficult task, and will necessarily involve a multi-sector approach. The purpose of this section is to address the two primary ways in which SimAotearoa can influence policy to help reduce obesity in Aotearoa New Zealand: first through utilising the SimAotearoa outputs for spatial analysis to help inform operational policy and service provision (Sub-section 7.3.1); and second to help inform policy more broadly.

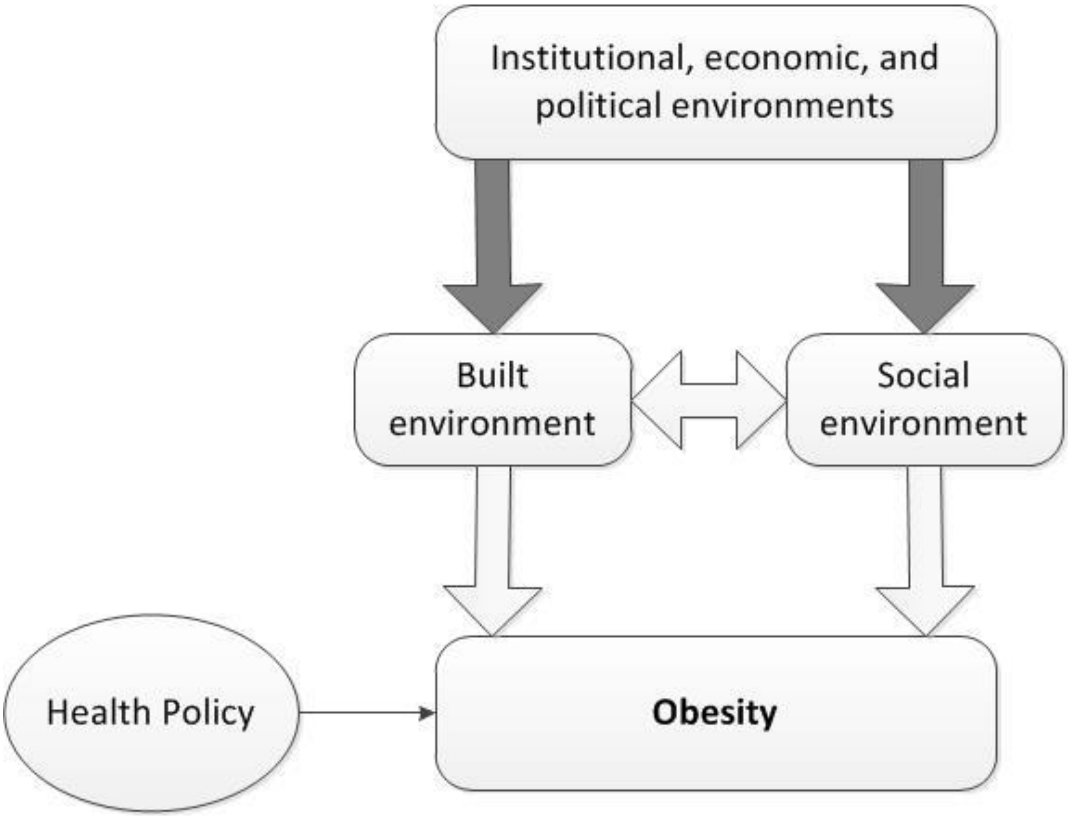


Figure 7.1: Why health policy alone is ineffective at reducing obesity, after Banwell (2017).

To develop a framework for informing policy, the key parts of the interacting system discussed previously (Section 7.2) have been pulled out as key targets for policy actions. From there, the ways in which each target might influence body size have been identified, along with possible policy responses, with example references in Table 7.1. From this table, selected items (marked with an asterisk) will be drawn out in the remaining Sub-sections: health strategy (Sub-section 7.3.2), the socio-economic environment (Sub-section 7.3.3), the built environment (Sub-section 7.3.4), and health in all policies (Sub-section 7.3.5).

Table 7.1: Key parts of the obesogenic environment.

Key targets	Modes of action	Possible policy responses	Example references
Obesity	Food Obesogenic environment Anti-fat bias in healthcare setting* Social stigma Victim blaming Maternal and infant nutrition	Alter the environment* Tax sugary food and drinks Target food advertising Regulate food content Favourable taxation of healthy food Food labelling Community gardens/alternate food supply Destigmatise obesity (especially in clinical settings)* Health promotion (may not work as intended)*	Kim and Kawachi (2006) Sacks, Swinburn, and Lawrence (2008) Swinburn and Egger (2002) Brownell et al. (2010) Adler and Stewart (2009) Davis, Ventura, Cook, Gyllenhammer, and Gatto (2011) Shapiro (2008) Thompson and Kumar (2011) Owen, Martin, Whincup, Smith, and Cook (2005)
Māori/Pacific Peoples	Differences in body size Structural racism (both within and outside health sector)* Disadvantaged by economic changes since 90s	Decouple relationship between Māori, Pacific Peoples and social deprivation* Recognise differing body structures* Culturally sensitive care Use a decolonising approach* Attendance to treaty obligations	Howden-Chapman (2015) Harris et al. (2012) Rush et al. (2009) Theodore et al. (2015) Came, McCreanor, Doole, and Simpson (2017)

Key targets	Modes of action	Possible policy responses	Example references
Social Deprivation	Stress* Increasing inequities since the 1990s Working conditions Housing Food security Structural inequity	Increase incomes* Improve working conditions (e.g. shift work, instability of hours, contract work) Employment policy State housing (accessibility/stability) Rental warrant of fitness Food banks Food in schools	Moore and Cunningham (2012) Pega et al. (2017) Schulte et al. (2007) Howden-Chapman (2015) Rush et al. (2007) Walton et al. (2013)
Built environment	Physical activity Public Transport/discourage car use Local amenity/walkability* Greenspace Neighbourhood safety	Access to primary care* Require consideration of health outcomes in local planning through RMA, LGA, and LTMA* Focus and improve walkability* Public Transport * Urban design/public space* Focus on making places healthy.	Barnett (2001) Stevenson, Banwell, and Pink (2006) Salmon (2015) Richardson et al. (2013)

Key targets	Modes of action	Possible policy responses	Example references
Intersections & interactions	Differential experience of disadvantage. Other forms of discrimination (e.g. disability, mental illness, gender, LGBTQIA+) 'Wicked problem'	Attendance to Patient's Context Work Across Policy Silos* Health in All Policies* Wellbeing/Hauora Food Aid Sent to The Pacific	Shapiro (2008) World Health Organisation and Government of South Australia (2010) Hughes and Lawrence (2005) Martin and Lippert (2012) Signal et al. (2013)

* Item will be included in subsequent sections.

7.3.1 Operational policy

Operational decisions, such as where to site new health care services, can be assisted by the simulated obesity estimates generated by SimAotearoa. Outputs can be fed into a more conventional geospatial model and used in spatial analysis. This could be useful for identifying locations with high obesity rates for targeted interventions, assessing demand for services, assessing service coverage, or predicting future demand; and potentially other uses as well.

No specific examples of analyses for operational decision-making are provided in this thesis. These types of analysis are best conducted with a specific question to ask, such as where a new treatment centre could be most effectively sited? This is partially because the decision that is eventually made will be constrained by practical considerations such as where land can be acquired. Consequently, it is better that this kind of analysis is conducted on an as-needed basis where all the applicable considerations can be taken into account. However, Sub-section 5.2.4 provides an example of how multiple variables can be used to identify an ‘at risk’ population that policy makers may wish to target.

It is also important for decision makers to be attentive to how institutional and operational policy decisions may differentially affect various groups and communities. Seemingly objective decisions may contribute to health inequities through unconscious and structural biases, as will be discussed later in this section. For example, primary care is predominantly structured as a private business in Aotearoa New Zealand, thus there could be a spatial bias in some circumstances away from poorer locations where inhabitants may be perceived to be less desirable customers, but conversely business premises in these areas are cheaper. There is some evidence that this does happen, particularly in rural areas (Brabyn & Barnett, 2004), though a more recent analysis does not support this (P. Beere Personal Communication). Though this may be a good business decision, it will likely contribute to worse health outcomes.

7.3.2 Health strategy

In recent years, the health sector in Aotearoa New Zealand has made many strides towards reducing structural inequities, particularly with respect to ethnicity. This has been thanks to the work of Mason Durie and others in challenging assumptions, investigating impacts, and re-formulating approaches in more appropriate ways (Durie, 2003; Durie, 2004; Durie, 1985;

Theodore et al., 2015; Warbrick et al., 2016). However more work is needed, not only with respect to ethnicity, but also to combat other forms of discrimination, such as heterosexism, cissexism, ableism, and fat phobia.

It is still common practice both clinically and within public health circles to place primary responsibility for body weight on individual patients (Ogden et al., 2001). Yet evidence indicates that the environment — particularly structural economic factors — has a greater influence over obesity than individual choices, though the impacts may not be the same among different places or countries (Egger & Swinburn, 1997). Stigmatisation of obesity does not motivate individuals to lose weight and negatively impacts on health outcomes and quality of care (Puhl & Heuer, 2010). Puhl and Heuer (2010) argue that any health promotion efforts should encourage healthy behaviours for everyone with a focus on good health rather than weight and discourage stigmatisation of obesity. However, even following these guidelines may still result in increased stigmatisation of obese individuals (Thompson & Kumar, 2011). Empathy training for medical students is also encouraged (Shapiro, 2008).

The stigma associated with obesity has a proportionally greater impact on Māori and Pacific Peoples, and thus this stigmatisation is not race-neutral. This interaction occurs partially because Māori and Pacific Peoples are over-represented among the those living in the most deprived areas, and partially because Māori and Pacific Peoples have lower percentages of body fat at the same BMI as a person of European descent (Rush et al., 2009). Though there are excellent statistical reasons for the decision to use the WHO categories for all ethnicities in Aotearoa New Zealand (for details see Ministry of Health, 2008a), it will necessarily increase the obesity stigma experienced by Māori and Pacific populations. A shift back to using ethnicity specific BMI categories is unrealistic, but it is important to educate clinicians on ethnic differences in body composition and encourage appropriate modulation of responses to patients on this basis.

The differential experience of obesity stigma by members of Māori and Pacific ethnic groups is also indicative of broader issues of structural racism in the health care sector. There is an onus on health care professionals and agencies to be attentive to the broader context in which in which ethnicity and obesity interact to magnify health inequities. The provision of sensitive, accessible, culturally appropriate care is essential for meeting Treaty of Waitangi obligations and reducing health inequities, as is a decolonising approach to health policy (Came et al., 2017; Fu, Exeter, & Anderson, 2015a; Signal et al., 2007). It is for this reason that Health Impact Assessment (HIA) in Aotearoa New Zealand includes consideration of the Treaty (Committee, 2005; Mathias & Harris-Roxas, 2009). Meeting these needs may have subtle flow on effects to obesity rates through the reduction of stress, though there is no clear association with obesity (Harris et al., 2012). Though ethnic minorities are often among the most visible, other forms of discrimination, such as heterosexism, can also have impacts on obesity and access to care (e.g. Austin et al., 2009).

7.3.3 Socio-economic environment

Structural racism is also a problem beyond the health sector and this contributes to making the environment in Aotearoa New Zealand obesogenic. Social deprivation is strongly linked to Māori and Pacific ethnic groups, meaning that these groups are disproportionately disadvantaged by the socio-economic gradient — including the health outcomes associated with low SES. Social welfare reforms since the 1990s have exacerbated this effect, by cutting beneficiary incomes and imposing stricter obligations on welfare recipients. (Howden-Chapman, 2015).

As mentioned in Sub-section 2.2.2, one of the major ways in which low SES contributes to obesity is through stress. As Moore and Cunningham (2012) demonstrate, ongoing chronic stress caused by structural and environmental factors can potentially have major impacts on obesity rates. Low SES can contribute to higher obesity risk through elevated exposure to chronic stress and associated behavioural and biological changes, such as changes in food consumption or elevated cortisol levels (Moore & Cunningham, 2012).

The environment generated by social, political, and economic conditions also promotes poor choices and limits the available options, particularly for those of low SES. For example, high housing costs limit discretionary household income, which restricts food budgets and causes stress; often lower cost housing is impractical or unavailable (Howden-Chapman, 2015). A small food budget promotes consuming cheaper food options which may have higher fat or sugar content relative to similar foods (Drewnowski, 2007; Rush et al., 2007). Further, the tendency to view obese individuals as ‘lazy’ or ‘lacking self-discipline’ promotes victim blaming and this may be internalised; reinforcement of negative stereotypes has a demonstrated negative effect on members of those groups (Puhl & Heuer, 2009). Some households in Aotearoa New Zealand experience persistent low SES (roughly one fifth of households with children), though most households experience low SES transiently — where the household experiences low SES only for a short period — as evidenced by Ball and

Wilson's (2002) study of children in benefit dependent households. Even short periods of low SES — particularly early in life — can have substantial effects over the life course.

The circumstances described above make obesity a trap that is difficult for those experiencing social deprivation to escape in Aotearoa New Zealand. No one would logically choose to be obese, but the circumstances of their lives eliminate viable alternatives. Consequently, policy strategies that alter the environment in which individuals make decisions may be a key component of obesity prevention efforts. Examples include: altering the taxation of food to favour healthier options, regulation of food content, or regulation of advertising (Kim & Kawachi, 2006; Sacks, Swinburn, & Lawrence, 2009). These kinds of actions need to be paired with strategies that reduce the stress associated with social deprivation and inequity such as making the social welfare system less punitive, ensuring that both workers and beneficiaries have enough to live on, and improving working conditions for low-paid workers (Schulte et al., 2007). Ensuring that there are realistic and accessible routes out of low SES through education, training, and other means is also essential.

7.3.4 Built environment

Enhancements to the built environment can also help to combat obesity. Much of this work is done at a local government level (TA and RC) rather than central government. Key areas of joint concern between local councils and public health officials include water quality, air quality, waste management, social connectedness, housing, and transport (e.g. Stevenson et al., 2006). These factors impact on public health in general, with housing and transport having a particular impact on obesity (see discussion in Sub-sections 2.3.3 and 2.3.4).

Currently, local planning rules for both RCs and TAs do not require a consideration of health outcomes. The Resource Management Act 1991 (RMA), in particular, is very process-oriented (K. Banwell personal communication); applications for development must demonstrate that they have followed certain procedures and met certain requirements. Modifying the legislation governing local planning processes — RMA, the Local Government Act 2002 (LGA) and the Land Transport Management Act 2003 (LTMA) — to require the impacts on the population and health outcomes to be considered could be beneficial in reducing obesity rates; at present some councils consider health impacts and some do not (Perkins & Thorns, 2001). Consideration of impacts and outcomes would mandate local government — whether RCs or TAs — to better consider the needs of local residents and the potential impacts policy may have on the wellbeing of citizens in a more holistic way.

Planning public transport is a complex exercise in Aotearoa New Zealand due to the number of different agencies involved. Officially, public transport is the responsibility of RCs. However, in practice TAs and often the New Zealand Transport Agency (NZTA) are involved. Further, the provision of public transport is usually through private companies. Each organisation has different priorities and goals, and there is often a delicate balancing act between cost and usage. At present, car use and road building are implicitly favoured over other modes of transportation (Early, Russell, Fougere, & Howden-Chapman, 2015). This has attendant consequences for health with respect to air quality, physical activity, and social connectedness, among others.

The pattern of urban development can also complicate the planning of transportation, as well as impact on citizen wellbeing. When commuter origins and destinations are dispersed widely across the city, as they were in Christchurch following the earthquakes in 2010 and 2011, it is difficult to design a public transportation system that can compete with private motor vehicles (Salmon, 2015). Consequently, where things are built — housing, businesses, roads — can have profound effect on the liveability and the wellbeing of residents. Urban design that favours local amenities, walkability, accessible public transport in a compact urban area is expected to provide healthier environments for residents.

7.3.5 Health in all policies

As argued above, many different factors influence obesity outcomes and health policy alone is likely to be insufficient to curb obesity. Further, anti-obesity health promotion efforts may not have the intended effect on population behaviour, as individuals often find ways to excuse themselves while blaming others for similar behaviours (Thompson & Kumar, 2011). Obesity has a broad and complex range of underlying causes — many outside of the influence of the health sector — and as a consequence — many current intervention strategies are ineffective, or have been discontinued (Theodore et al., 2015). It is essential that responses to obesity use a multi-sector approach that works across policy silos. The need to address obesity in a holistic manner is already well established in existing literature (e.g. Lang & Rayner, 2007; Sacks et al., 2009; Signal et al., 2013; Swinburn et al., 2011c). Thus, because many kinds of policies can influence obesity outcomes, assessing the health impacts of all policies may encourage better consideration of the unintended impacts on population health both for obesity and wellbeing in general. This approach is called 'Health in All Policies' or HiAP (World Health Organisation & Government of South Australia, 2010).

The *Adelaide Statement on Health in All Policies* describes the approach as assisting "leaders and policy-makers to integrate considerations of health, well-being and equity during the development, implementation and evaluation of policies and services" (World Health Organisation & Government of South Australia, 2010, p. 2). The statement includes descriptions of when HiAP works best, in essence when there is a clear mandate and effective processes to work across sectors and with multiple stakeholders. The statement also gives a list of tools and instruments useful for HiAP in different parts of the policy cycle, including: ways of working across policy silos, health lens analysis, and impact assessments. One of the challenges of implementing a HiAP approach is that the health sector must learn to work alongside other sectors in order to achieve its own goals.

Though leadership from central government on HiAP would be beneficial, planning processes at a local government level can still utilise HiAP processes to good effect. An example of this in Aotearoa New Zealand is the use of HIA on the Greater Christchurch Urban Development Strategy (UDS), a process which deliberately included engagement with Māori and assessed the potential health impacts of the UDS in a number of areas (Stevenson et al., 2006). The impact of the HIA on the UDS was later evaluated and found to have demonstrable direct and indirect effects on the final version of the UDS with the majority of the HIA recommendations being adopted by the UDS (Mathias & Harris-Roxas, 2009). Several organisations associated with the UDS continue to use HiAP (Healthy Christchurch, n.d.).

Epp (1986, pp. 427-428) states: "*we cannot invite people to assume responsibility for their health and then turn around and fault them for illnesses and disabilities which are the outcome of wider social and economic circumstances.*" Yet, fundamentally, obese individuals are blamed for their weight, the key determinants of which (e.g. environmental factors, SES) are often out of their control. Individuals make choices about their health and wellbeing in a context not of their own choosing (Cockerham, 2005), anti-obesity policy must reflect this, and support appropriate decision making in a non-judgemental way (Adler & Stewart, 2009).

7.4 Summary: Model, society, and policy

The purpose of this chapter was to address Objective 5: to evaluate and critique the outputs and potential uses of SimAotearoa. This chapter has drawn together all of the preceding results and discussed them with respect to existing literature and ideas. To some extent, this has also been a space in which to critique an approach with which I no longer agree — having come to the realisation that, at face value, the results simply reinforce existing structural inequities. Thus, this discussion has examined the simulation and results from a perspective far removed from that typically used to assess quantitative research. As a result, this discussion has been wide ranging, including a technical discussion of the model, an assessment of how different forms of disadvantage may interact with obesity both socially and spatially, and an analysis of the policy implications.

Stigmatisation of obesity does not help individuals to lose weight. Anti-fat stigma, along with other forms of discrimination, is among the forces that negatively impacts on an individual's health. Public Health researchers speak from a position of authority and relative power. Though Public Health researchers are responsible for reducing the harm caused by obesity, they should take care not to further stigmatise populations that may already be marginalised on a variety of axes.

By the standards of a SMSM, SimAotearoa has been demonstrated to provide robust small area estimates of obesity rates, despite a number of limitations. Many of the limitations can be minimised by sensitive and appropriate use of the results. SimAotearoa outputs can be used by policy makers for operational decision-making, but can also inform policy in a broader sense.

Chapter 8 Conclusion

The aim of this thesis was to put population level adult obesity in Aotearoa New Zealand into a social and spatial context using SMSM. This thesis has made a number of original contributions to knowledge, including providing the first estimates and maps of obesity in small areas throughout Aotearoa New Zealand both for current data and future projections. Small area estimates were produced for: (1) obesity in the overall population, (2) obesity in a number of key population subgroups, (3) diabetes rates, and (4) obesity projections for 2018 and 2023. The results show that obesity in Aotearoa New Zealand is highly clustered, with the highest obesity areas confined primarily to areas of high deprivation mediated by age and ethnicity. The spatial distribution of obesity varies somewhat among population subgroups, though the overall pattern generally can still be seen. This thesis has also described and demonstrated a modification of an existing methodology, by creating a national model which restricts the microdata used based on location.

This final chapter highlights the key findings and original contributions made by this thesis. Included are avenues of future research, and recommendations based on the thesis outcomes. The chapter will begin by summarising the research objectives and their outcomes (Section 8.1), before outlining the key points raised throughout the thesis (Section 8.2), along with potential future avenues of research (Section 8.3), and a number of recommendations (Section 8.4). The thesis concludes with a final summary (Section 8.5).

8.1 Evaluation of research objectives

There were five key objectives to guide this research. This section evaluates the success of these objectives with reference to the relevant sections of the thesis.

The first objective was to review the literature around obesity and obesogenic environments, and the use of spatial microsimulation for health purposes. This was primarily addressed through the literature review in Chapter 2, that covered a background on SMSM along with a brief background of obesity, its causes, and ways of understanding it — including obesogenic environments. Some supporting information in terms of the Aotearoa New Zealand context was also supplied in Chapter 3.

The second objective was to develop a spatial microsimulation model (SimAotearoa) suitable for estimating adult obesity and diabetes at a small area level in the Aotearoa New Zealand population in 2013; and to test the validity of this model. This was successfully achieved and described in Chapter 4, which shows the process for building and validating SimAotearoa.

The third objective was to develop a spatial microsimulation model (SimAotearoa) that estimates future adult obesity rates based on 2018 and 2023 population projections; and to test the validity of this model. This was successfully achieved and the process of building and validating the projected obesity model was described in Chapter 6.

The fourth objective was to explore the results of both static and projected spatial microsimulation models for obesity, diabetes, and key population subgroups, including how these results may be potentially relevant to policy. This objective was primarily addressed in Chapter 5, which examined the results of SimAotearoa. The projected model portion of this objective was addressed in Chapter 6, and the policy responses were addressed in the discussion (Section 7.3).

The fifth objective was to evaluate and critique the outputs and potential uses of SimAotearoa. This was addressed through the discussion in Chapter 7. It was found that SimAotearoa has many potential uses, but caution must be exercised in order to avoid reproducing existing inequities.

8.2 Key points

Section 8.1 evaluated the research objectives, describing how and where the thesis has addressed each of these. This section moves beyond the thesis objectives to highlight the key points made by the thesis and the new contributions to knowledge.

This thesis has found that obesity is confined to a restricted subset of areas, primarily associated with high deprivation and mediated by age and ethnicity (see Section 5.2). The very strong association between obesity and deprivation suggests that obesity may be an intractable problem unless steps are taken to address the impact of social deprivation on body weight. Significant clusters of high obesity rates were found in Northland, South Auckland, Waikato, East Cape, Porirua, and Lower Hutt; though high obesity rates were also found in other areas. Conversely, obesity rates were lowest in wealthy urban areas such as Central Auckland. Obesity rates amongst Māori are very high at CAU scale, though the spatial pattern of distribution is similar to the overall population. Rates of obesity amongst Pacific

Peoples are also high at CAU scale, but the spatial distribution is more even and does not display the significant clustering seen in the Māori and overall populations. Amongst young adults, CAU scale obesity rates were low in rural areas and high in urban areas while still showing evidence of the overall pattern of obesity being associated with deprivation.

SimAotearoa showed a wide range of obesity rates among CAUs —some areas had extremely high rates (up to 67.2%) while others had very low rates (as low as 15.3%). Obesity was strongly related to deprivation, with areas of high and low obesity largely divided by deprivation (79.0% convergence). However, there were some clear exceptions and this relationship is not static across the country at either DHB or CAU scale. Little change is expected to the estimated obesity rates in 2018 and 2023 compared with 2013 — based on demographic projections — though a slight divergent trend is present. Consequently, health inequities with respect to obesity are currently high and are expected to increase.

Standard statistical methods are unable to provide detailed, small area estimates or analysis. Standard methods will necessarily miss small pockets with different obesity status to the regional population, due to the larger areas used in standard analyses for practical reasons (Openshaw, 1984a). While standard methods are more robust than SMSM, the detailed, spatially specific small area estimates available in SimAotearoa offer a useful tool to policy makers.

8.3 Future research

Section 8.2 discussed the key findings of the thesis, and what has been learned about obesity in Aotearoa New Zealand. This section uses that base to discuss how this work could be extended in future by first looking at further uses of the existing model, then by examining future data or improved methods. Possible avenues for future work include additional analysis of the existing outputs, as well as taking steps that would further test the limits of and potentially improve the SMSM itself.

Utility of the existing SimAotearoa outputs could be extended in several ways. Firstly, the outputs could be used to assess provision or distribution of obesity related services either nationally or within a smaller area, to improve service provision. This possibility has been discussed in Sub-section 7.3.1, but no such analysis is included here as it is outside of the scope of this research. Secondly, the CAU level obesity estimates could be used to investigate spatial relationships between obesity and other environmental variables (e.g. greenspace, food outlets). Thirdly, the CAU level obesity prevalence data could be combined with other environmental data in a multi-level model to investigate obesity at different spatial scales.

Rebuilding the model using 2018 Census data and future NZHS data is advised for several reasons: first, it would update the estimates provided to the latest data; second, it would enable some assessment of the accuracy of the projected models; and third, the 2018 Census will use the new smaller SA1 output areas (Stats NZ, 2017b), which should give a more fine-grained picture of obesity in Aotearoa New Zealand (though this may not be backwards compatible to SimAotearoa). It may also be beneficial to use data on underlying health issues rather than body size.

Another key future task would be to further test the utility and implications of the microdata restriction method. The benefit of microdata restriction was discovered late in the model building process, and has not been tested in combination with other methods to improve the quality of the simulation outputs. In particular the model may benefit from repeating the variable selection process and modelling with *k*-means (Smith et al., 2009) within a restricted data paradigm. Additionally, a more systematic approach could be taken to developing the groupings of DHBs used for microdata restriction.

There are many technical improvements that could be made to the model itself that may change the outputs. This includes building the model using 2-way (e.g. Tanton & Vidyattama, 2010; Vidyattama & Tanton, 2013) rather than 1-way constraint tables, or using different modelling methodologies (e.g. Ballas et al., 2005b; Tomintz, Kosar, & García-Barrios, 2017). Such improvements could potentially improve the accuracy of the synthetic data set, and thus improve its utility for policy analysis. Some of these possible changes would involve using stochastic processes that have been avoided throughout this thesis due the potential to introduce changes in the results on separate runs of the model, however some of these issues can be mitigated by using a static seed for generating random numbers.

Other possible future improvements would alter the scope of the model and the project. These could include adding children to the model, incorporating environmental variables (e.g. greenspace or food outlets) into the model, or using a dynamic aging methodology, which would provide the opportunity to assess underlying changes in the obesity rate over time, or how past events may affect future health status (Dekkers, 2015). Modelling households rather than individuals may enable the examination of more complex relationships such as whether obesity status of an individual may be correlated with the obesity status of other members of the household (e.g. Ballas et al., 2005a; Rossiter, Ballas, Clarke, & Dorling, 2009). Another consideration might be exploring alternatives to BMI or how the results could be adjusted to mitigate the known biases from its use (see Sub-section 2.1.4).

8.4 Recommendations

The previous section discussed how this research could be extended and improved on in the future. This section expands upon that discussion to give recommendations that should be considered by policy makers and other researchers.

The strong relationship between obesity and social deprivation would suggest that reducing inequity is a key anti-obesity measure. This study is not able to make clear the exact nature of the relationship between obesity and deprivation. However, the degree of clustering seen in the obesity results and congruence between obesity and deprivation suggests that addressing social deprivation and inequity are essential in order to reduce the extreme rates of obesity observed in areas of low SES (see Section 7.2).

Addressing inequity is not a recommendation that can be acted on solely in a health context. It requires a whole of government approach, and may be best achieved by taxation or other structural changes that would facilitate individuals making healthier choices of their own accord (Brownell et al., 2010). Health policy approaches that may be beneficial include encouraging the use of HIAs on a broad range of policy, reducing inequities in health service provision and access, and encouraging local government agencies to support healthy environments (see Section 7.3). In addition, the education of medical professionals to reduce the stigmatisation and blame placed on obese patients in the short term may help to improve patient outcomes (Shapiro, 2008).

The obesity outputs generated through SimAotearoa have been made available to the Ministry of Health. The scope of analysis for which the SimAotearoa outputs have been used in this thesis was necessarily limited, but the capacity is there to use these results for policy making now and into the future. As with any piece of research, its utility only really comes through its application in a real-world context.

There is some evidence to suggest that anti-obesity policy and strategies could be made at different spatial scales depending on the population sub-group targeted. For example, obesity among Māori was highly clustered, and varied among DHBs. Locally developed strategies targeted within a specific region might more effectively target the specific local conditions.

Conversely, obesity among Pacific Peoples was more evenly spread and these groups may be more effectively targeted as a single group, or as specific sub-groups for each island nation (e.g. Samoan, Tongan etc.) due to their strong community ties. Either of these approaches may be inefficient or inappropriate for practical reasons, but they could be worth investigating. If they are already in use, then this research supports their continuation.

The results of SimAotearoa showed that obesity is highly clustered, and though a large DHB region may have a low rate of obesity, there may still be pockets within the region with very high rates of obesity. It is critical that a DHB with a low overall obesity rate, such as Central Auckland, still engage in anti-obesity programmes. This phenomenon — the modifiable areal unit problem — is well known within geography, but may be less familiar to public health professionals (Openshaw, 1984b). The power of SMSM is that it enables policy makers to see and understand the spatial patterning of obesity in more detail, and respond with more precision to the heterogenous spatial distribution of obesity.

8.5 Final word

Obesity is a complex issue — socially, medically, politically — and one that has real impacts on the lives of individuals. The hyperbolic 'obesity epidemic' headlines described at the beginning of this thesis do little to address the reality that the impacts of obesity are not evenly spread in the population, either socially or spatially. There is scant evidence to suggest — either from SimAotearoa or elsewhere — that obesity related health inequities will improve in the short term.

The aim of this thesis was to put population level adult obesity in Aotearoa New Zealand into a social and spatial context using SMSM. The contributions made by this thesis have been achieved chiefly by providing fine scale estimates of obesity in Aotearoa New Zealand. The estimates produced for obesity in 2013 at CAU level are novel, and not available through other sources. They represent a new tool for policy makers for operational decision making adding a level of spatial granularity not previously available in Aotearoa New Zealand. Though the restriction of microdata has been tested before (Tanton & Vidyattama, 2010), in SimAotearoa such restriction was critical to the modelling process, and provided further insights into the workings of SMSM in a Aotearoa New Zealand context.

Evaluating the results of SimAotearoa through the lens of Aotearoa New Zealand's social context has also been critical to understanding obesity in Aotearoa New Zealand. Adding spatial information to this evaluation improves existing knowledge of the relationship between social deprivation and obesity in Aotearoa New Zealand. Knowledge is not produced in a vacuum; there are structural inequities which operate through normal social and economic processes in order to produce the spatial patterns modelled in this thesis. Reflecting on the social context in which SimAotearoa was constructed has made a deeper contribution to knowledge of obesity and contextualised the model beyond what would be possible in simply reporting the results.

Chapter 9 References

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Appendices

Appendix A Maps of deprivation and census data

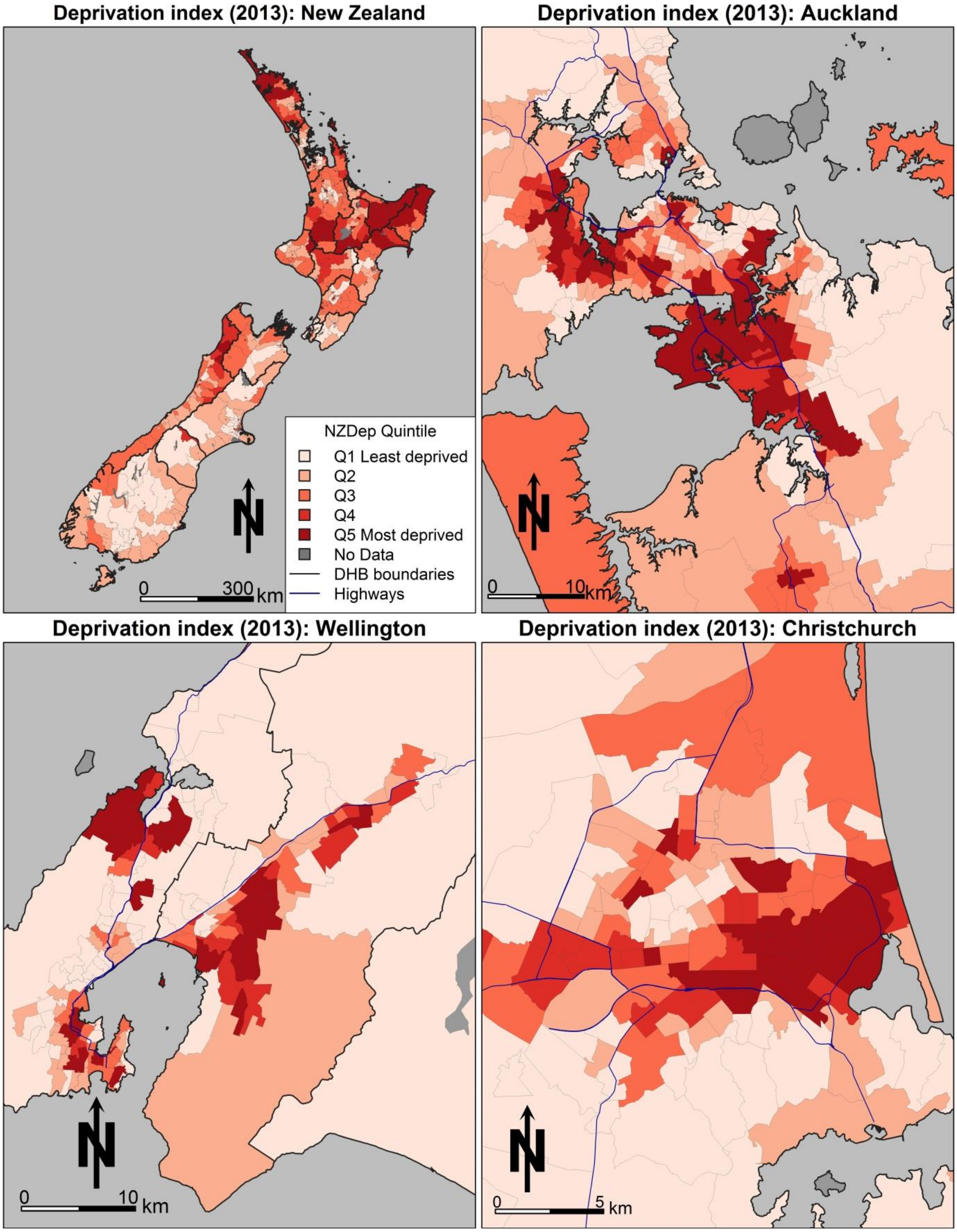

Figure A.1: Deprivation by CAU

Data for Figure A.1 from Atkinson et al. (2014)

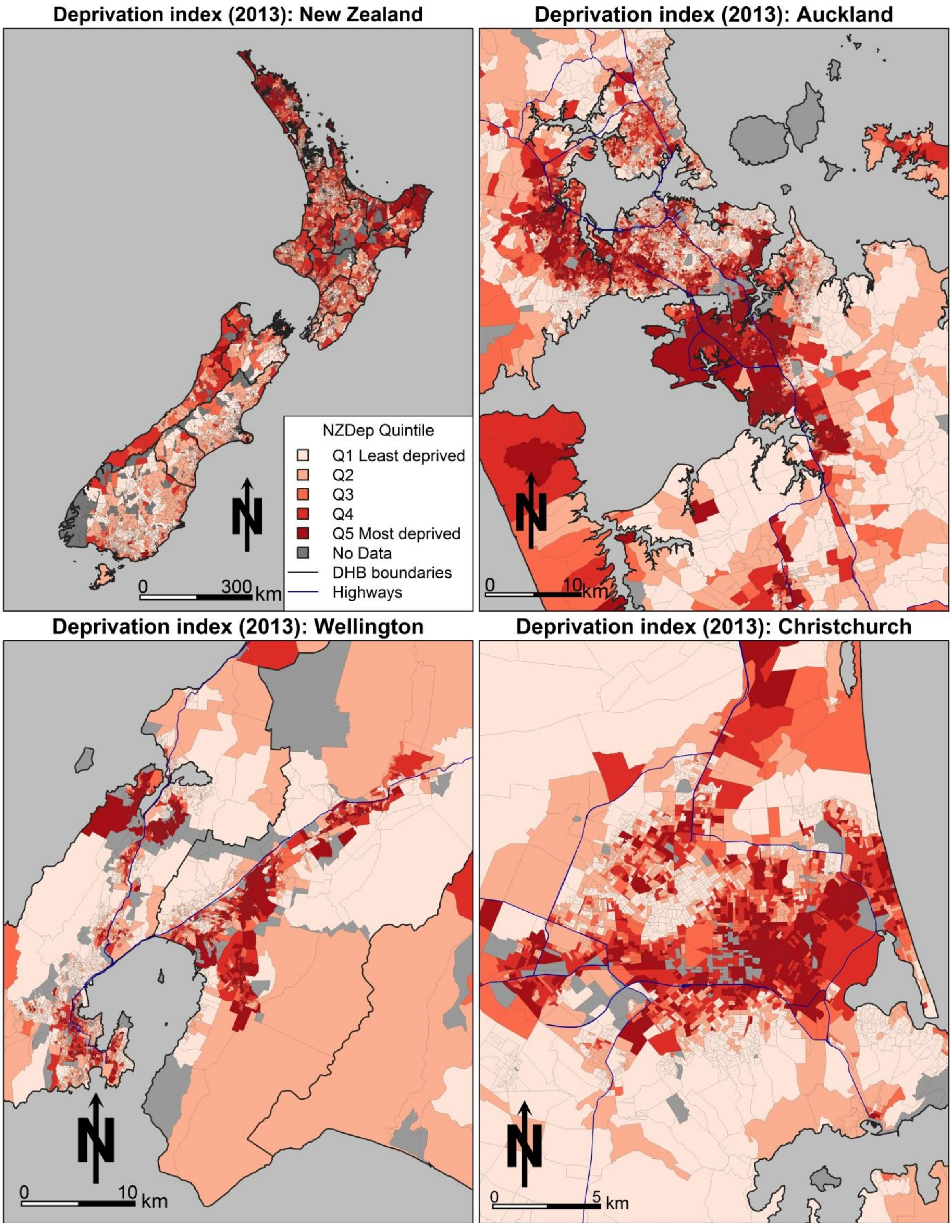

Figure A.2: Deprivation by MB

Data for Figure A.2 from Atkinson et al. (2014)

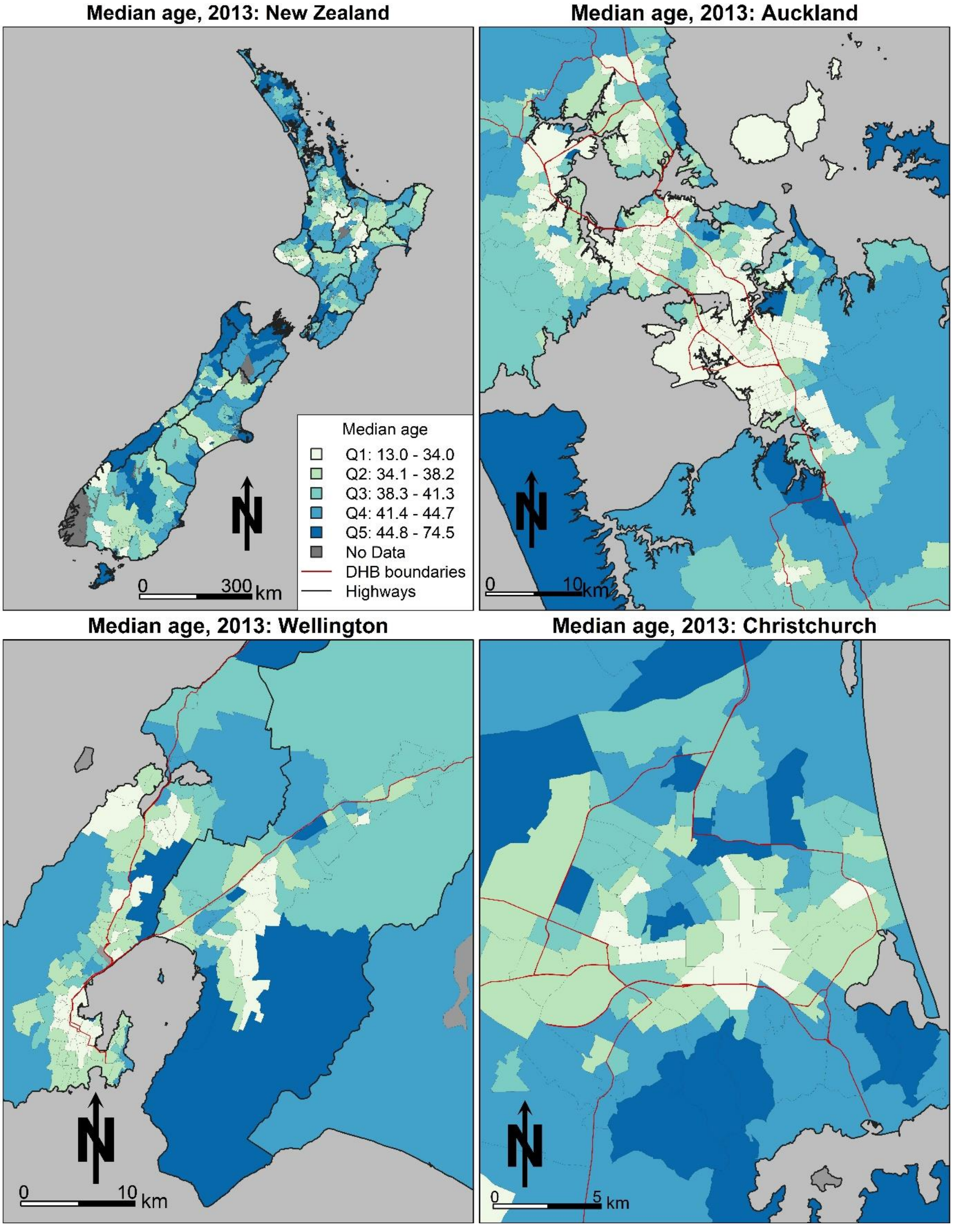

Figure A.3: Median age in CAUs from census 2013 data

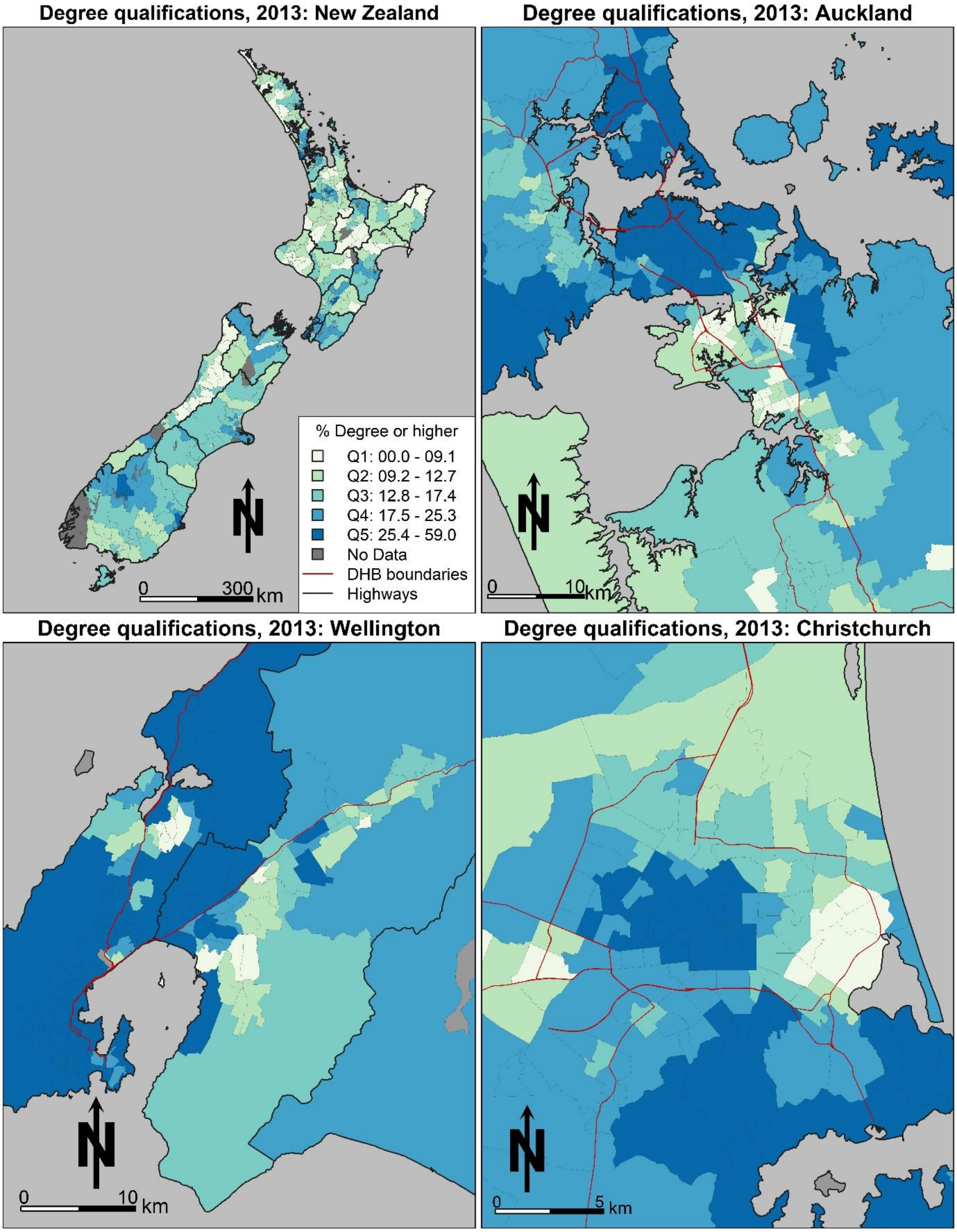

Figure A.4: Degree qualification in CAUs from census 2013 data

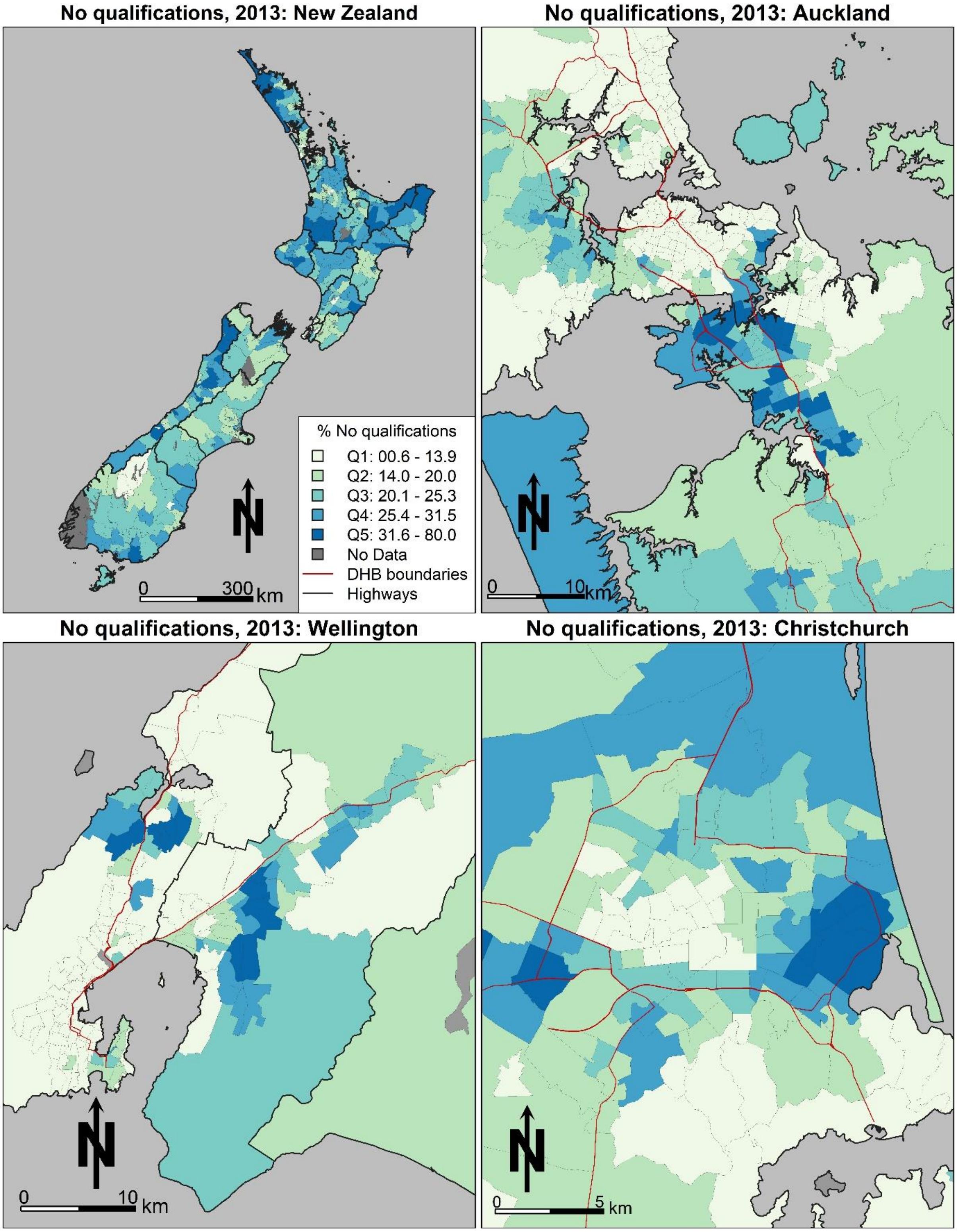

Figure A.5: No qualification in CAUs from census 2013 data

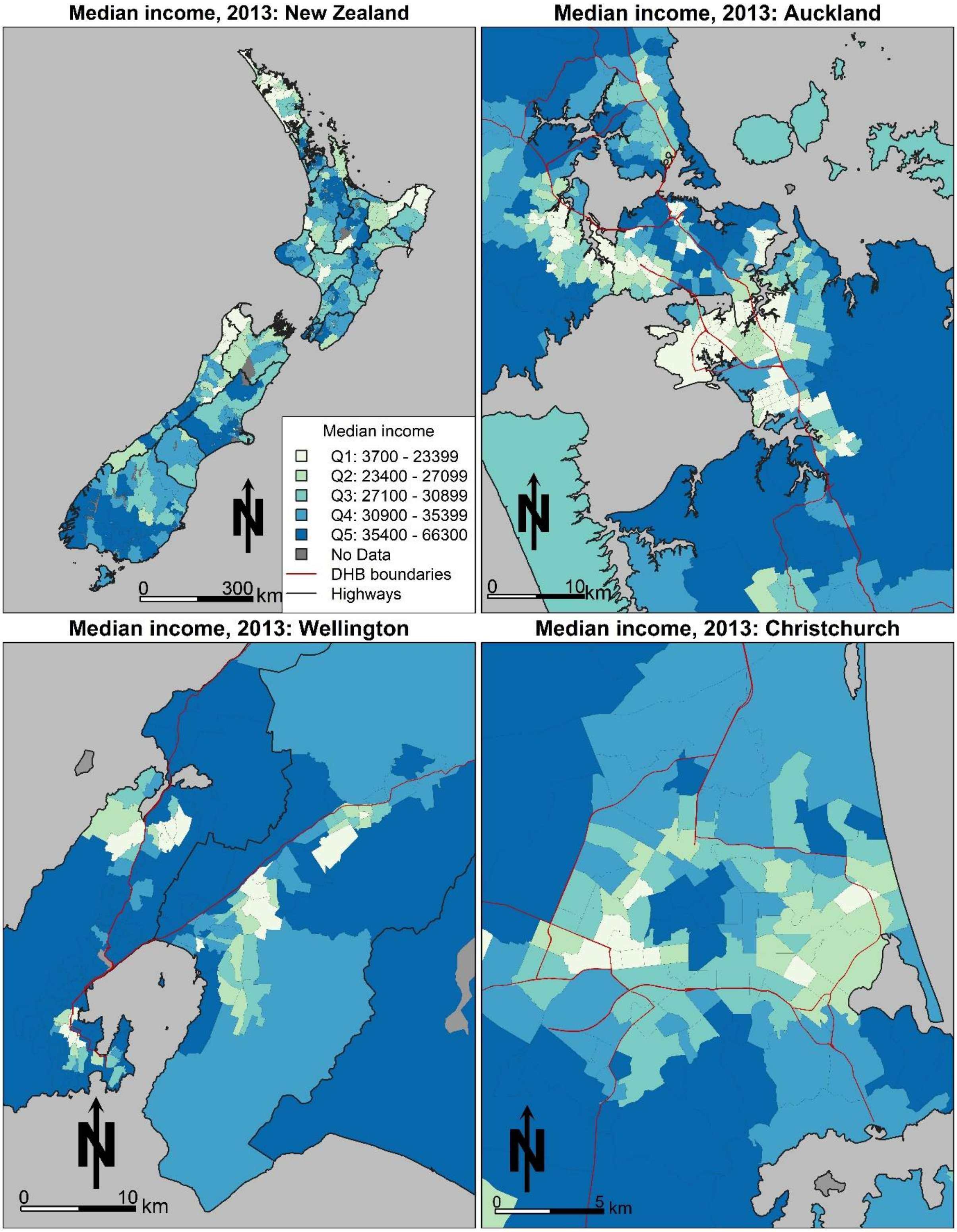

Figure A.6: Median income in CAUs from census 2013 data

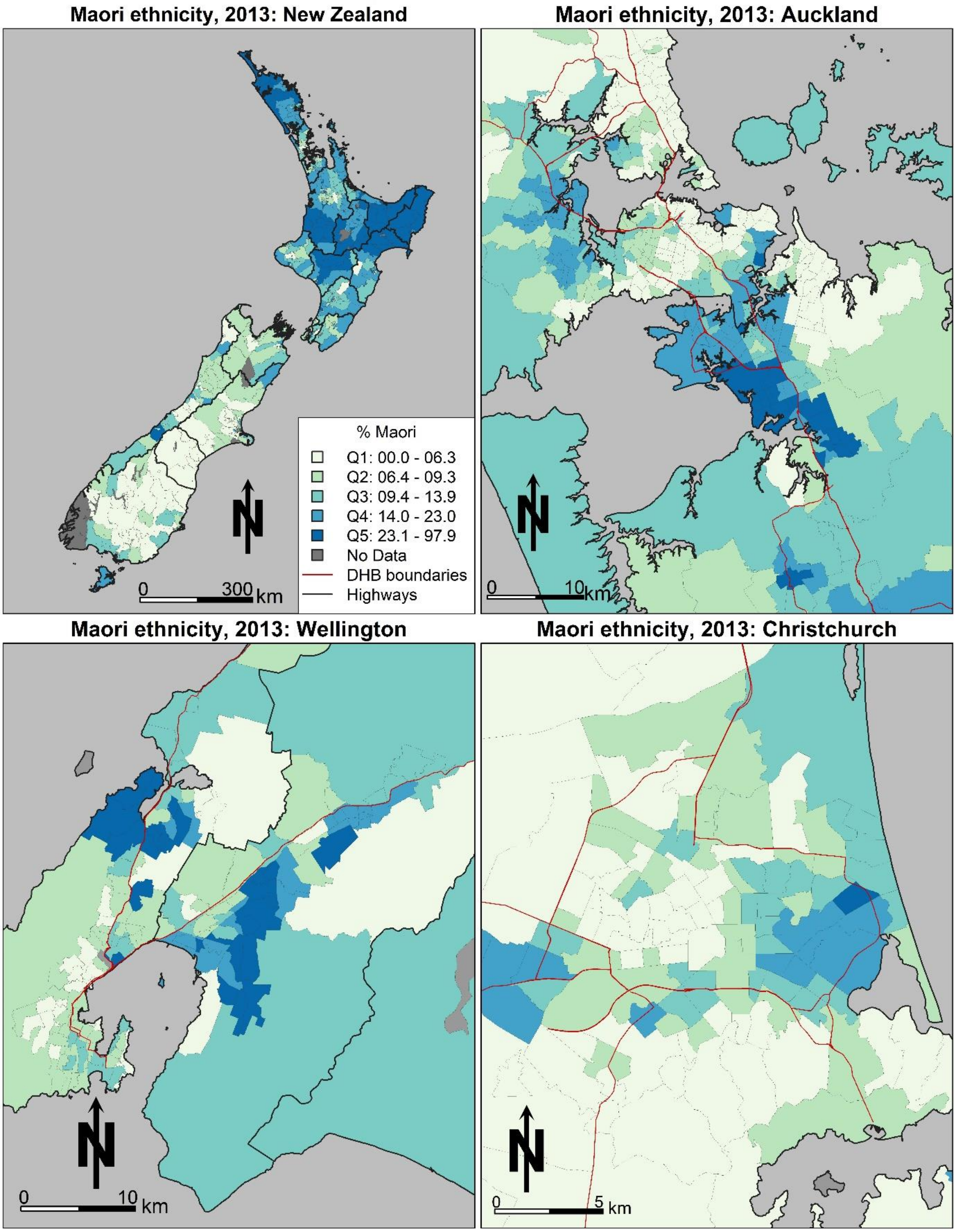

Figure A.7: Maori ethnicity in CAUs from census 2013 data

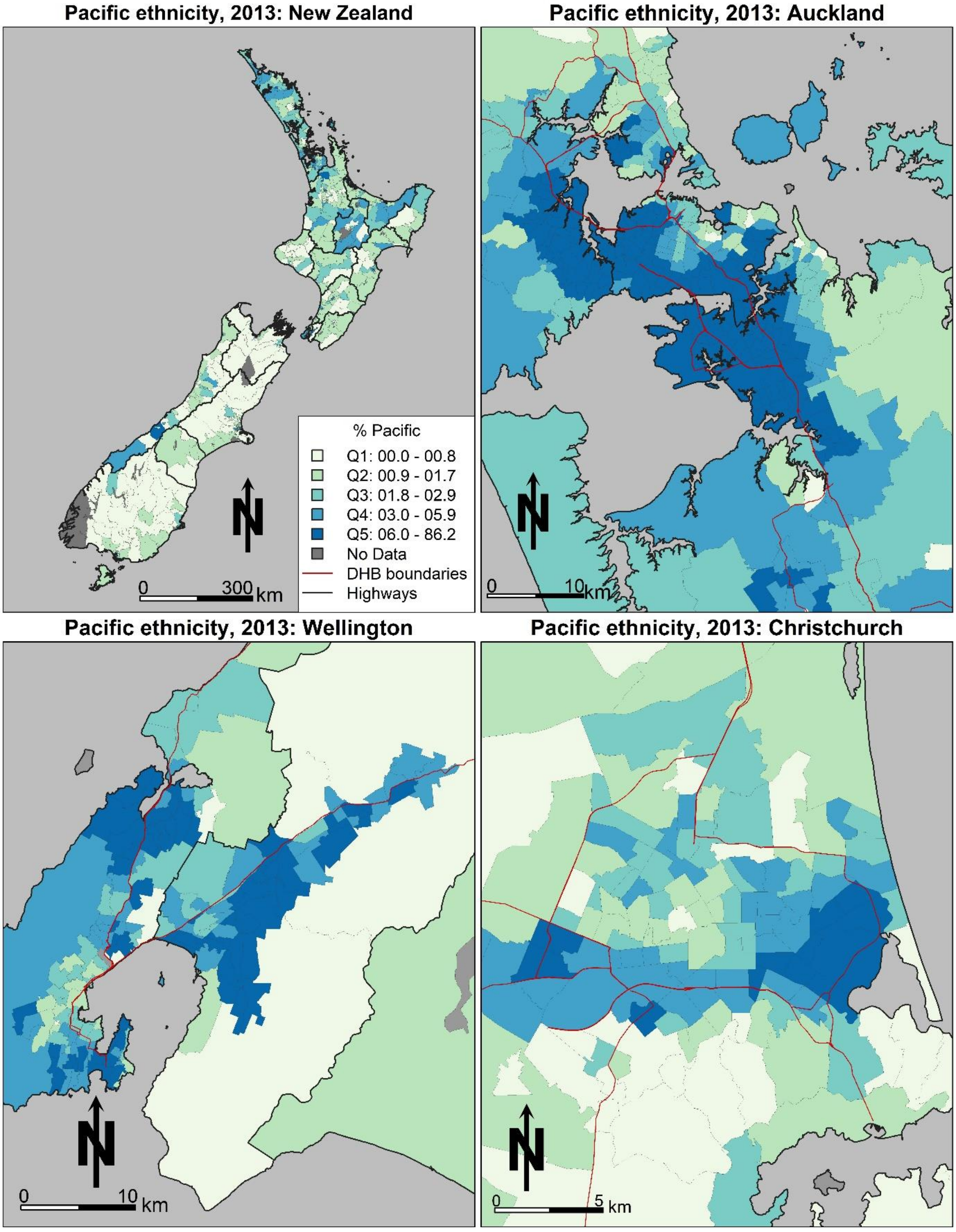

Figure A.8: Pacific ethnicities in CAUs from census 2013 data

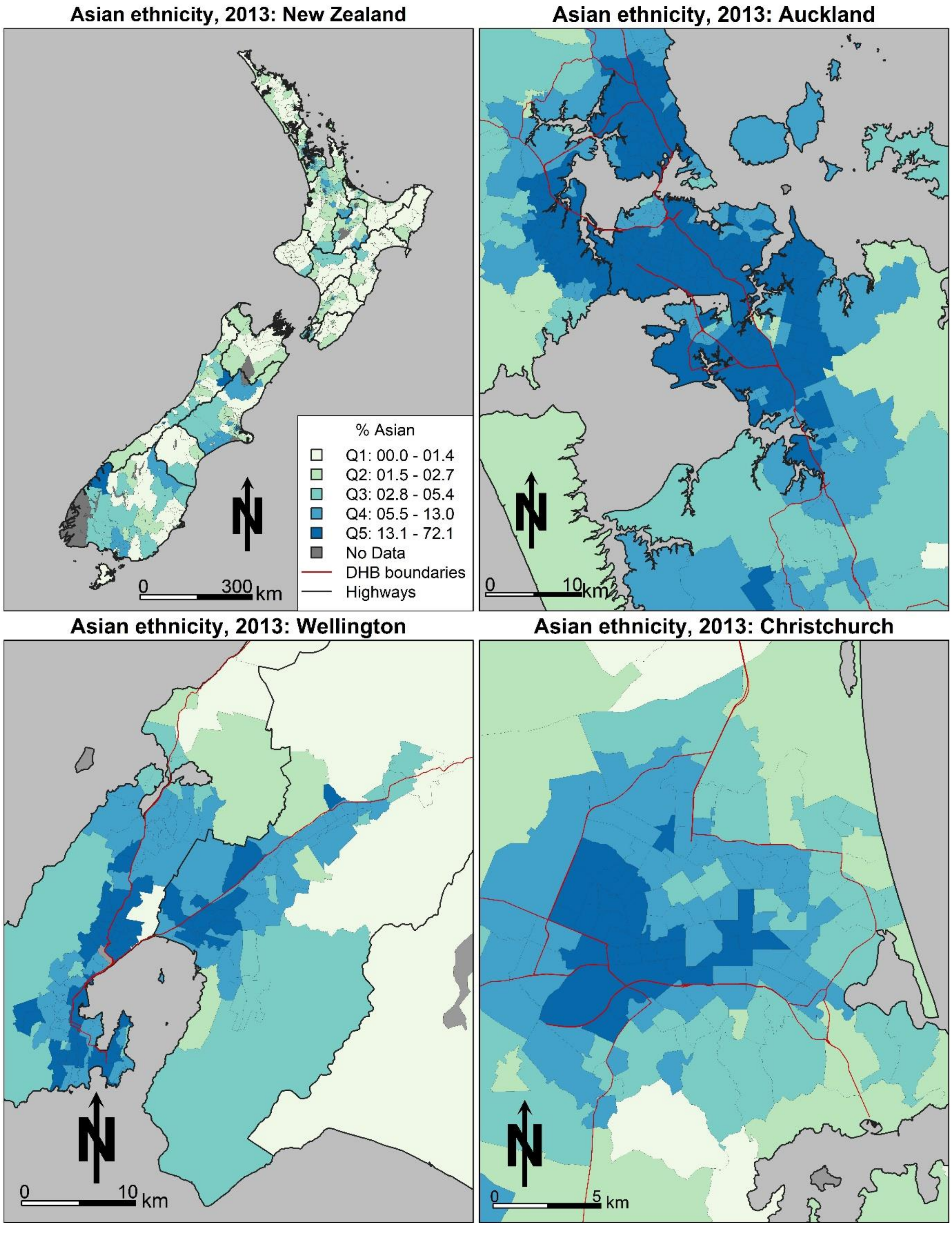

Figure A.9: Asian ethnicities in CAUs from census 2013 data

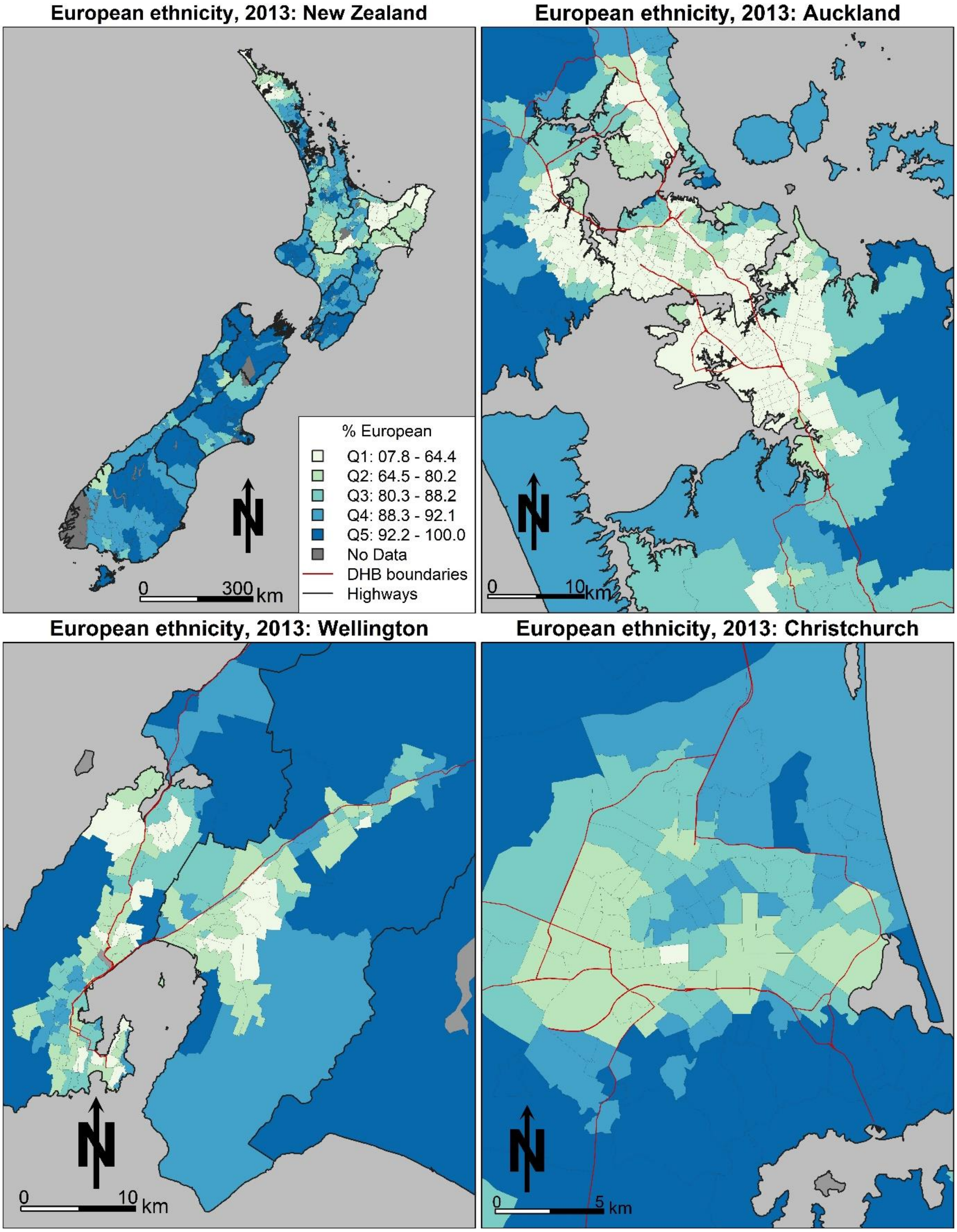

Figure A.10: European ethnicities in CAUs from census 2013 data

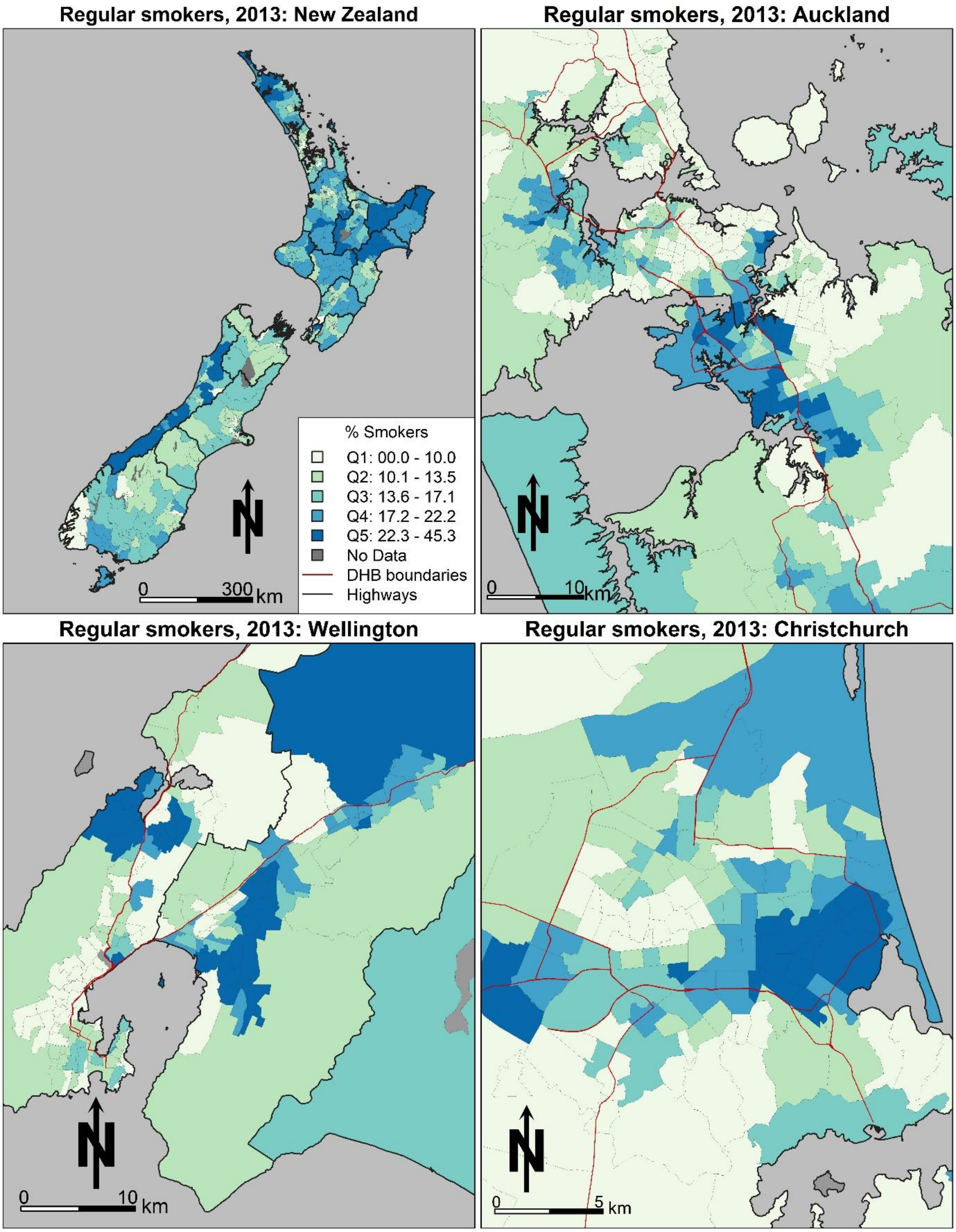

Figure A.11: Regular smokers in CAUs from census 2013 data

Appendix B SMSM code

```
###########################
### SMSM Reweighting file
###########################

###########################################
## Import census data for use in validation

censusSMvalid <- read.csv("C:/Local/AFW44/PAPER
    3/censusData_wScaled_FINAL.csv", header=T, row.names=1)
read.csv("censusData_raw_URpop_depCorr.csv", header=T, row.names=1)
ageStart <- which(colnames(censusSMvalid) == "A15.19")
colnames(censusSMvalid)[seq(ageStart, ageStart+14)] <-
    as.character(unique(lookupAge[,"ageCen"]))

censusSMvalid <- censusSMvalid[rownames(areaF),]

## Add "Not" variables for SMSM error check
censusSMvalid[,paste("Not", varEth)] <- censusSMvalid[,"EthStated"]
    - censusSMvalid[,varEth]
censusSMvalid[,"Not Maori"] <- ifelse(censusSMvalid[,"Not Maori"] <
    0, 0, censusSMvalid[,"Not Maori"])
censusSMvalid[,"Not Pacific"] <- ifelse(censusSMvalid[,"Not
    Pacific"] < 0, 0, censusSMvalid[,"Not Pacific"])
censusSMvalid[,"Not Asian"] <- ifelse(censusSMvalid[,"Not Asian"] <
    0, 0, censusSMvalid[,"Not Asian"])
censusSMvalid[,"Not European"] <- ifelse(censusSMvalid[,"Not
    European"] < 0, 0, censusSMvalid[,"Not European"])

## Move all the scaled variables to the primary variable so that eth
    stated < total pop etc doesn't cause huge errors
for (i in c(varEth, paste("Not", varEth))){
```

```
censusSMvalid[,i] <- ifelse(censusSMvalid[,i] *
    censusSMvalid$QualTotal/censusSMvalid$EthStated >
    censusSMvalid$QualTotal, censusSMvalid$QualTotal,

     censusSMvalid[,i] *
    censusSMvalid$QualTotal/censusSMvalid$EthStated)
}
if("ten" %in% ls()){
    for (i in c(varTen)){
     censusSMvalid[,i] <- censusSMvalid[,paste0(i, "Sc")]
}}
if("lfs" %in% ls()){
    for (i in c(varLFS)){
     censusSMvalid[,i] <- censusSMvalid[,paste0(i, "Sc")]
}}

if (substr(varAge[1], 1, 2) == "AC") {
    for (i in varAge){
     censusSMvalid[,i] <-
    rowSums(censusSMvalid[,as.character(lookupAge[lookupAge$AgeCat3
    == i, "ageCen"])], na.rm=T)
    }
}


## This function calculates the total of the new area weights for
    each variable
## and applies them to the storage array
calcWeights <- function(regTotals, yDim){
    ## loop over all variables
    for (i in 1:length(varConcor)){
     ## loop over all levels for this variable
     for (j in
    unlist(varConcor[i])[2:length(unlist(varConcor[i]))]) {
          ## subset all individuals with this characteristic
          query <- micro[micro[,unlist(varConcor[i])[1]] == j , ]
          ## sum their weights (vector of all areas)
```

```
            if (dim(query)[1] > 1) {
                  regTotals[rownames(areaF), j] <-
     colSums(SMweights[query$CharID, rownames(areaF), yDim], na.rm=T)
                  } else {
                  regTotals[rownames(areaF), j] <-
     SMweights[query$CharID, rownames(areaF), yDim]
                  }
      }
     }
     return(regTotals)
}

#####################
#Start reweighting
#####################

## declare outside of loop
exEr <- 0
modEr <- 0
smallEr <- 0
tinyEr <- 0

#areaStore <- areaF
#microStore <- micro

## 20 iterations
for (k in 1:20){
## handle each DHB separately
for (n in DHBlist){
micro <- microStore[microStore$DHBname == n,]
areaF <- areaStore[areaStore$DHBname == n,]
     ## loop over each variable set
     for (i in 1:length(varConcor)){
      ## loop over all areas
      for (m in rownames(areaF)){
            ## loop over all the levels within the current variable
```

```
        for (j in
    unlist(varConcor[i])[2:length(unlist(varConcor[i]))]) {
                ## For each variable level, calculate the scaling
    variable (based on the individuals characteristics) * old weight
    for this individual
                ## scaling variable (real area totals from
    census/simulated totals from summing weights or, initially,
    tabulating micro data)
                SMweights[micro$CharID,m,i+1] <- ifelse(micro[,
    unlist(varConcor[i])[1]] == j, SMweights[micro$CharID,m,i] *
    (areaF[m, j]/areaEsts[m,j,i]), SMweights[micro$CharID,m,i+1])
      }}
      ## copy the estimates back to the start to loop through the
    next variable
      areaEsts[, , i+1] <- calcWeights(areaEsts[,,i+1], i+1)
}}

## Copy weights and estimates back to start
areaEsts[,,1] <- areaEsts[,,i+1]
SMweights[,,1] <- SMweights[,,dim(SMweights)[3]]

## End of iteration error estimation: Estimate - Census
## Will be inaccurate for ethnicity due to non response (not
    stated), excludes some areas not in census data (low population)
for (l in varnames){ areaErrors[rownames(censusSMvalid),l] <-
    round(areaEsts[rownames(censusSMvalid),l,i+1] -
    censusSMvalid[,l], digits = 2) }

## combine current estimate with raw error and % error
pop.Er <- rbind(areaEsts[1,,i+1], areaErrors[1,],
    areaErrors[1,]/sum(censusSMvalid[1,c("M", "F")])*100)
rownames(pop.Er) <- c("Est Popn", "Raw error", "% error")
print(pop.Er)

## Provide indication of degree of innaccuracy
exEr <- table(abs(areaErrors) > 20)["TRUE"]
modEr <- table(abs(areaErrors) > 10)["TRUE"]
```

```
smallEr <-table(abs(areaErrors) > 5)["TRUE"]
tinyEr <- table(abs(areaErrors) > 1)["TRUE"]

exPer <- (exEr/(dim(areaErrors)[1]*dim(areaErrors)[2]))*100 #%
    extreme error (>|20%|)
modPer <- (modEr/(dim(areaErrors)[1]*dim(areaErrors)[2]))*100 #%
    moderate error (>|10%|)
smallPer <- (smallEr/(dim(areaErrors)[1]*dim(areaErrors)[2]))*100 #%
    moderate error (>|5%|)
tinyPer <- (tinyEr/(dim(areaErrors)[1]*dim(areaErrors)[2]))*100 #%
    moderate error (>|1%|)
print (paste0("1%: ", tinyPer, ", 5%: ", smallPer, ", 10%: ",modPer,
    ", 20%: ", exPer))
}
```

Appendix C Additional validation results

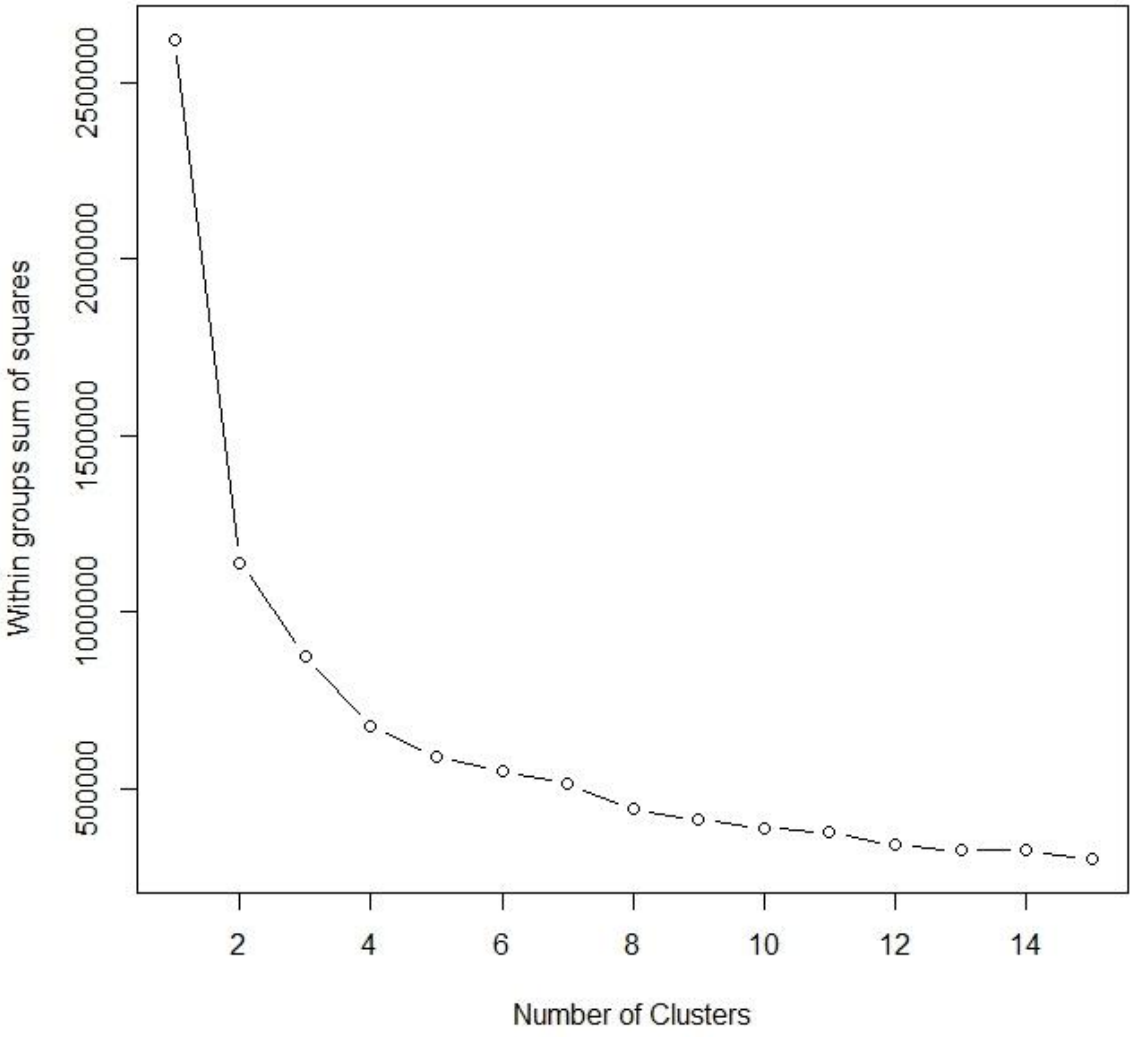

Figure C.1: Within group sums of squares, used for assessing how many clusters to use.

Table C.1: Full cluster descriptions.

	Cluster			
	1	**2**	**3**	**4**
M	47.65	48.98	49.17	48.14
F	52.36	51.04	50.86	51.91
Maori	21.55	11.51	8.82	38.12
Pacific	4.43	7.18	1.41	19.72
Asian	6.28	24.64	3.97	9.61
European	75.94	61.28	89.34	43.76
Q1	2.20	14.90	30.28	0.17
Q2	6.11	24.80	27.66	0.99
Q3	15.97	27.52	23.92	2.04
Q4	35.02	25.94	15.78	11.66
Q5	40.69	6.84	2.35	85.14
NoQual	25.66	13.85	18.87	28.18
School	33.82	36.70	35.60	32.84
Trade	16.02	15.07	19.44	11.86
Uni	10.69	23.50	16.69	7.55
QualRef	13.78	10.88	9.34	19.53
Own	47.56	40.07	59.96	33.45
Rent	52.44	59.95	40.05	66.48
Employed	57.17	64.70	67.24	49.56
Unemployed	6.02	5.04	3.10	9.60
NILF	36.80	30.30	29.65	40.87
A15-19	8.66	8.99	7.80	11.11
A20-24	8.49	11.39	6.07	10.27
A25-29	7.52	10.48	5.68	8.49
A30-34	7.17	10.08	6.18	7.68
A35-39	7.49	8.91	7.57	7.80
A40-44	8.28	9.12	9.53	8.49
A45-49	8.29	8.42	9.88	8.33
A50-54	8.71	7.86	10.22	8.58
A55-59	7.87	6.64	9.05	7.34

	Cluster			
	1	**2**	**3**	**4**
A60-64	7.22	5.52	8.27	6.63
A65-69	6.20	4.19	6.95	5.23
A70-74	4.96	3.07	5.04	4.14
A75-79	3.71	2.20	3.36	2.76
A80-84	2.90	1.62	2.38	1.84
AOver85	2.54	1.53	2.02	1.30
Regular	21.59	13.58	13.71	28.41
Ex	25.23	19.20	25.79	20.38
Never	53.22	67.20	60.49	51.22

Table C.2: External validation of clusters for never smoked category

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Cluster 1									
Mean	7.07	6.57	6.28	6.17	6.08	6.10	6.21	7.39	6.37
Median	7.04	6.66	5.55	5.77	5.82	5.78	6.14	7.15	6.25
Spread	0.03	0.09	0.73	0.40	0.25	0.32	0.07	0.24	0.12
Std Error	8.10	8.15	10.42	8.65	8.65	8.43	7.89	9.27	8.01
Minimum	0.11	0.17	0.07	0.00	0.13	0.00	0.01	0.04	0.00
Maximum	22.32	22.95	28.75	23.90	25.10	22.49	21.69	26.84	23.06
TAE	42,250	39,173	40,106	37,379	37,526	36,907	36,989	44,254	37,819
% SAE >20%	0.35	0.35	1.06	0.71	0.71	0.71	0.35	0.71	0.35
Cluster 2									
Mean	8.70	7.89	11.85	8.82	8.70	8.69	7.83	9.73	7.90
Median	8.69	7.99	12.19	9.01	8.75	8.89	7.92	9.55	7.98
Spread	0.01	0.10	0.34	0.20	0.04	0.21	0.09	0.18	0.09
Std Error	10.14	9.89	16.79	11.69	11.31	11.25	9.86	11.52	9.86
Minimum	0.37	0.06	0.20	0.00	0.02	0.01	0.10	0.80	0.26
Maximum	37.80	40.36	30.48	39.79	34.83	39.59	39.62	41.53	39.56
TAE	68,446	63,191	100,188	72,568	71,503	71,202	62,817	76,246	62,814
% SAE >20%	1.04	0.35	6.94	0.69	0.69	0.69	0.35	1.74	0.69

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Cluster 3									
Mean	6.25	5.71	5.51	5.24	5.63	5.20	5.41	6.49	5.47
Median	6.27	5.63	5.10	4.92	5.42	4.87	5.26	6.34	5.33
Spread	0.02	0.08	0.41	0.32	0.21	0.33	0.14	0.15	0.14
Std Error	3.16	3.21	3.53	3.21	3.32	3.18	3.15	3.61	3.14
Minimum	0.00	0.00	0.00	0.01	0.02	0.00	0.01	0.01	0.01
Maximum	40.96	40.69	40.29	39.51	40.35	39.39	39.39	45.51	39.37
TAE	111,483	103,328	102,485	95,541	103,375	94,624	98,086	118,537	98,754
% SAE >20%	0.46	0.28	0.28	0.28	0.28	0.28	0.28	0.37	0.28
Cluster 4									
Mean	9.02	8.53	9.64	7.65	8.82	8.21	7.99	9.20	8.26
Median	9.14	8.99	6.40	7.25	6.93	8.33	8.38	9.54	8.66
Spread	0.12	0.47	3.24	0.40	1.90	0.13	0.39	0.34	0.40
Std Error	11.96	10.96	27.05	15.21	17.01	12.91	10.86	12.69	10.94
Minimum	0.06	0.70	0.02	0.02	0.15	0.00	0.05	0.25	0.63
Maximum	22.17	25.45	29.72	25.35	29.78	24.33	23.82	27.82	23.55
TAE	35,261	32,507	47,614	32,120	39,607	33,517	30,923	35,826	31,637
% SAE >20%	0.99	0.99	15.84	0.50	9.90	0.50	0.50	0.99	0.99

Table C.3: External validation of clusters for ex smokers.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Cluster 1									
Mean	2.71	3.06	2.83	2.78	2.78	2.77	2.82	2.70	2.84
Median	2.61	3.03	2.60	2.63	2.66	2.62	2.76	2.64	2.80
Spread	0.09	0.04	0.23	0.15	0.12	0.15	0.06	0.05	0.04
Std Error	2.88	3.08	3.47	3.07	3.05	3.05	2.89	2.83	2.90
Minimum	0.02	0.04	0.00	0.03	0.01	0.02	0.01	0.00	0.03
Maximum	8.12	8.44	8.56	8.46	8.54	8.37	8.73	8.51	8.95
TAE	14,866	16,988	16,398	15,530	15,639	15,443	15,470	14,708	15,577
% SAE >20%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cluster 2									
Mean	3.35	4.18	5.17	4.37	4.08	4.32	3.86	3.89	3.84
Median	3.17	4.14	5.24	4.34	4.11	4.21	3.77	3.77	3.84
Spread	0.18	0.04	0.07	0.03	0.02	0.11	0.09	0.12	0.00
Std Error	4.63	5.15	7.51	5.98	5.38	5.85	5.00	4.97	4.96
Minimum	0.04	0.04	0.05	0.12	0.00	0.04	0.02	0.11	0.04
Maximum	16.36	17.12	13.72	16.92	15.32	17.00	17.01	16.72	17.09
TAE	25,058	32,140	42,439	34,399	31,872	33,908	29,536	29,761	29,460
% SAE >20%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Cluster 3									
Mean	2.99	3.79	3.51	3.42	3.59	3.40	3.52	3.56	3.55
Median	2.61	3.53	3.22	3.17	3.34	3.14	3.25	3.29	3.29
Spread	0.38	0.26	0.30	0.25	0.25	0.27	0.27	0.27	0.26
Std Error	1.44	1.78	1.83	1.74	1.76	1.72	1.71	1.72	1.71
Minimum	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.01
Maximum	21.61	22.72	21.78	21.67	21.91	21.76	21.94	20.57	20.34
TAE	45,456	61,665	58,291	55,974	58,732	55,523	57,163	57,920	57,450
% SAE >20%	0.09	0.19	0.19	0.19	0.19	0.19	0.19	0.09	0.19
Cluster 4									
Mean	3.70	3.93	4.16	3.83	4.03	3.92	3.80	3.61	3.88
Median	3.52	3.91	3.44	3.86	3.57	3.97	3.83	3.62	3.87
Spread	0.18	0.02	0.72	0.04	0.46	0.06	0.03	0.01	0.01
Std Error	5.20	4.85	7.92	5.33	6.35	5.38	4.65	4.45	4.60
Minimum	0.00	0.02	0.04	0.00	0.09	0.02	0.10	0.03	0.05
Maximum	11.09	9.44	11.37	11.18	10.58	11.26	11.34	12.00	11.35
TAE	13,768	14,389	17,945	14,444	15,993	14,700	13,632	12,702	13,820
% SAE >20%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table C.4: External validation of clusters for regular smokers.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Cluster 1									
Mean	4.82	4.21	4.28	4.11	4.02	4.05	4.06	5.22	4.16
Median	5.07	4.21	3.60	3.99	3.80	3.99	3.96	5.20	4.10
Spread	0.25	0.01	0.68	0.11	0.22	0.07	0.10	0.02	0.06
Std Error	6.38	6.38	8.05	6.84	6.85	6.64	6.32	7.71	6.35
Minimum	0.13	0.02	0.07	0.05	0.06	0.01	0.00	0.01	0.07
Maximum	20.39	20.48	25.34	21.63	22.49	20.56	19.90	24.96	20.65
TAE	29,071	24,681	26,485	24,383	24,466	24,032	23,903	31,377	24,464
% SAE >20%	0.35	0.35	0.35	0.35	0.35	0.35	0.00	0.35	0.35
Cluster 2									
Mean	5.80	4.25	7.21	5.07	5.23	4.98	4.54	6.25	4.54
Median	5.64	4.00	6.89	4.75	4.79	4.72	4.23	5.71	4.16
Spread	0.16	0.25	0.33	0.32	0.44	0.26	0.31	0.54	0.37
Std Error	6.38	5.85	10.22	6.98	7.19	6.66	6.16	7.97	6.18
Minimum	0.10	0.10	0.28	0.04	0.02	0.12	0.01	0.01	0.01
Maximum	21.05	22.85	23.30	22.48	19.12	22.21	22.22	24.42	22.07
TAE	44,290	31,890	58,530	39,135	40,522	38,225	34,177	47,182	34,184
% SAE >20%	0.35	0.35	0.35	0.35	0.00	0.35	0.35	0.35	0.35

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Cluster 3									
Mean	4.18	3.07	3.17	3.01	3.16	3.00	3.05	3.79	3.04
Median	4.17	2.76	2.67	2.58	2.75	2.56	2.65	3.57	2.70
Spread	0.01	0.31	0.50	0.43	0.40	0.44	0.39	0.22	0.34
Std Error	2.13	1.85	2.08	1.90	1.97	1.89	1.87	2.29	1.85
Minimum	0.00	0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.01
Maximum	20.61	19.24	19.78	19.11	19.70	18.89	18.72	27.14	20.36
TAE	73,534	51,198	54,133	50,238	53,772	49,895	50,923	67,356	50,820
% SAE >20%	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.09
Cluster 4									
Mean	5.72	5.10	6.61	4.52	5.72	4.93	4.74	6.02	4.95
Median	5.64	4.84	5.27	3.97	4.57	4.69	4.61	5.89	4.74
Spread	0.08	0.26	1.34	0.55	1.15	0.24	0.13	0.13	0.21
Std Error	8.19	7.42	20.45	11.60	11.85	8.86	7.62	9.89	7.63
Minimum	0.02	0.01	0.08	0.01	0.08	0.04	0.02	0.23	0.02
Maximum	21.08	22.21	26.03	22.76	24.03	21.97	21.59	25.96	21.26
TAE	21,862	18,625	31,475	18,697	24,685	19,661	17,911	23,473	18,486
% SAE >20%	0.50	0.50	2.48	0.50	0.50	0.50	0.50	0.50	0.50

Table C.5: Full analysis of restricted model external validation errors

	Never smoked						Ex smoker						Regular smoker					
	STD (2y)	FULL (3y)	DHB	CITY	DEP	RURAL	STD (2y)	FULL (3y)	DHB	CITY	DEP	RURAL	STD (2y)	FULL (3y)	DHB	CITY	DEP	RURAL
National																		
Mean	6.19	6.18	6.35	5.22	4.54	5.90	3.50	3.50	3.81	3.18	2.83	3.63	3.62	3.59	3.65	3.16	2.99	3.33
Median	5.98	6.00	5.83	4.66	4.11	5.74	3.30	3.29	3.30	2.79	2.37	3.31	3.31	3.23	3.07	2.71	2.51	2.95
Spread	0.21	0.18	0.52	0.56	0.44	0.16	0.20	0.21	0.51	0.39	0.46	0.32	0.31	0.36	0.58	0.44	0.47	0.38
Std Er	3.12	8.71	8.78	7.11	8.31	9.04	1.49	2.81	2.52	2.55	2.86	3.15	2.05	7.52	8.24	6.00	7.05	7.94
Min.	0.01	0.00	0.00	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max.	39.62	40.68	46.51	39.05	36.14	38.35	21.94	21.59	32.63	19.54	23.94	21.45	22.22	23.05	24.25	22.13	21.57	22.06
TAE	228817	227530	217421	188622	159682	213482	115802	116244	117884	103508	86934	117191	126914	125344	117757	104709	97117	113834
% SAE >20%	0.32	0.00	0.00	0.00	0.00	0.00	0.11	0.00	2.33	0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.00	0.00
Northland																		
Mean	9.38	9.22	6.50	8.38	6.77	8.58	4.02	4.06	3.91	3.91	2.83	3.74	5.43	5.25	2.71	4.60	4.19	4.99
Median	9.57	9.42	6.43	8.56	6.74	8.46	4.40	4.40	4.03	4.09	2.82	3.84	5.27	4.98	2.55	4.39	4.04	4.84
Spread	0.20	0.20	0.07	0.18	0.03	0.13	0.38	0.34	0.12	0.18	0.01	0.10	0.17	0.28	0.16	0.22	0.15	0.15
Std Er	9.06	9.25	11.37	7.57	7.06	8.24	3.89	3.88	6.55	4.01	3.31	3.76	6.41	6.70	7.68	5.27	5.51	6.24
Min.	0.21	0.01	0.20	0.06	1.43	0.05	0.02	0.04	0.04	0.10	0.03	0.08	1.68	1.28	0.17	0.01	0.45	1.37
Max.	14.68	14.54	15.16	14.66	13.04	14.89	9.10	9.20	12.26	10.37	8.98	9.93	12.42	12.41	6.83	10.64	10.77	11.93
TAE	33494	32993	23368	30208	23984	30266	14714	14785	14328	14364	10115	13459	19121	18575	9314	16219	14658	17428
% SAE >20%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Waitemata																		
Mean	6.93	7.06	6.38	5.05	4.40	6.11	2.82	2.79	3.13	2.26	1.78	2.52	4.17	4.32	3.38	3.06	2.97	3.73
Median	6.78	6.99	6.15	4.83	4.21	5.90	2.89	2.85	3.29	2.16	1.65	2.42	4.49	4.56	3.28	3.25	2.93	3.78
Spread	0.15	0.07	0.22	0.21	0.18	0.22	0.07	0.06	0.16	0.10	0.13	0.10	0.32	0.24	0.10	0.19	0.03	0.05
Std Er	9.70	9.55	10.47	8.81	7.30	8.99	5.09	5.11	5.44	4.88	4.03	4.90	5.31	5.14	6.08	4.76	4.48	4.90
Min.	3.58	3.50	1.96	0.55	1.11	2.54	0.02	0.03	0.11	0.00	0.05	0.00	1.09	0.94	0.03	0.08	0.09	0.77
Max.	10.69	10.99	11.41	9.97	8.53	11.01	6.99	6.96	8.18	5.89	5.23	7.45	8.08	8.61	9.40	7.01	6.20	7.51

	Never smoked						Ex smoker						Regular smoker					
	STD (2y)	FULL (3y)	DHB	CITY	DEP	RURAL	STD (2y)	FULL (3y)	DHB	CITY	DEP	RURAL	STD (2y)	FULL (3y)	DHB	CITY	DEP	RURAL
TAE	11213	11308	10152	8108	7202	10216	4374	4327	4958	3496	2807	4227	6865	7005	5320	4961	4942	6143
% SAE >20%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Auckland																		
Mean	5.29	5.26	4.64	4.65	4.25	5.65	3.97	4.05	3.10	3.59	3.55	4.63	2.45	2.37	2.47	2.33	2.33	2.28
Median	4.71	4.80	4.07	3.86	3.56	5.01	3.67	3.73	2.54	3.11	2.98	4.40	2.12	1.98	2.11	1.84	1.84	1.84
Spread	0.58	0.47	0.57	0.79	0.69	0.64	0.30	0.32	0.56	0.48	0.57	0.24	0.32	0.40	0.36	0.49	0.48	0.44
Std Er	14.57	14.66	13.88	14.95	11.36	12.66	8.60	8.80	10.14	9.56	7.86	8.60	9.27	9.90	5.82	8.40	6.99	8.12
Min.	0.01	0.01	0.03	0.10	0.01	0.21	0.08	0.13	0.03	0.03	0.02	0.10	0.00	0.03	0.04	0.01	0.01	0.02
Max.	15.81	16.19	16.21	13.89	15.33	16.12	21.05	21.42	21.55	19.54	23.94	21.45	10.89	11.22	12.61	11.72	9.34	10.07
TAE	22260	22121	19679	18778	17134	23019	15334	15571	11494	13333	12960	17435	9814	9522	10183	8876	8965	9145
% SAE >20%	0.00	0.00	0.00	0.00	0.00	0.00	0.48	0.48	0.48	0.00	0.48	0.48	0.00	0.00	0.00	0.00	0.00	0.00
Counties Manukau																		
Mean	6.95	6.82	5.41	5.79	4.84	6.77	2.73	2.80	2.43	2.71	2.37	3.13	4.54	4.35	4.24	3.67	3.44	4.08
Median	6.62	6.64	4.74	5.56	4.41	6.37	2.57	2.63	1.91	2.38	1.90	2.82	4.21	3.95	3.98	3.52	2.90	3.64
Spread	0.33	0.18	0.67	0.23	0.43	0.40	0.17	0.18	0.52	0.33	0.47	0.31	0.32	0.41	0.26	0.15	0.54	0.44
Std Er	12.84	12.66	8.73	13.61	9.38	10.53	6.86	6.87	5.77	6.69	5.68	6.04	6.77	6.64	5.61	7.75	5.03	5.67
Min.	0.37	0.53	0.00	0.34	0.00	0.10	0.01	0.02	0.00	0.01	0.03	0.01	0.23	0.11	0.15	0.31	0.06	0.16
Max.	16.45	16.48	16.49	16.33	14.62	17.17	11.08	10.62	10.29	8.97	7.96	11.22	12.84	13.03	10.34	10.68	10.31	11.92
TAE	17232	17002	12999	13970	12120	16600	5847	5960	5119	5389	4918	6467	11655	11324	10489	9248	8777	10560
% SAE >20%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Waikato																		
Mean	8.40	8.30	5.89	8.25	5.85	7.35	4.81	4.90	3.26	4.79	3.80	4.72	3.81	3.64	3.12	3.80	2.40	2.89
Median	8.52	8.43	5.73	7.67	5.62	7.22	4.89	4.95	3.03	4.96	3.70	4.72	3.86	3.53	3.02	3.21	2.28	2.81
Spread	0.12	0.13	0.17	0.58	0.23	0.13	0.08	0.05	0.23	0.17	0.10	0.00	0.05	0.11	0.10	0.59	0.12	0.08
Std Er	10.37	10.39	10.38	8.82	8.50	9.80	4.47	4.50	5.10	4.48	4.16	4.81	7.09	7.20	6.90	5.76	5.79	6.71
Min.	0.73	0.22	0.64	0.43	0.01	0.70	0.26	0.38	0.11	0.10	0.05	0.02	0.01	0.11	0.05	0.01	0.00	0.00
Max.	19.67	20.34	17.96	21.53	17.62	18.16	10.55	10.50	11.06	11.49	10.70	11.25	10.73	11.21	9.34	11.50	10.46	11.51

	Never smoked						Ex smoker						Regular smoker					
	STD (2y)	FULL (3y)	DHB	CITY	DEP	RURAL	STD (2y)	FULL (3y)	DHB	CITY	DEP	RURAL	STD (2y)	FULL (3y)	DHB	CITY	DEP	RURAL
TAE	30842	30431	20589	30092	20871	26371	16799	17090	10420	16687	12562	15841	14227	13565	11203	13832	8840	10826
% SAE >20%	0.00	0.72	0.00	0.72	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Lakes																		
Mean	5.41	5.50	9.78	4.12	3.77	5.01	2.81	2.80	5.71	2.41	2.13	2.86	3.32	3.42	4.67	2.75	2.51	2.98
Median	5.46	5.46	9.09	3.79	3.39	5.12	2.59	2.51	5.28	2.10	1.84	2.71	2.82	3.03	4.32	2.19	1.73	2.27
Spread	0.05	0.03	0.70	0.33	0.38	0.12	0.22	0.28	0.43	0.31	0.29	0.16	0.50	0.39	0.35	0.56	0.78	0.70
Std Er	6.84	6.96	5.87	5.96	5.26	6.47	3.44	3.49	2.95	3.29	2.94	4.01	4.89	5.05	5.58	4.15	4.16	4.48
Min.	0.12	0.06	2.45	0.07	0.02	0.38	0.16	0.10	1.05	0.01	0.02	0.00	0.02	0.18	0.33	0.11	0.02	0.05
Max.	14.29	14.09	21.39	12.77	13.97	14.17	8.50	8.48	14.98	9.21	7.28	7.99	12.59	13.62	14.96	12.69	12.43	12.59
TAE	6168	6269	11428	4388	3848	5611	2887	2887	6160	2539	2042	2947	3628	3725	5437	2546	2517	3196
% SAE >20%	0.00	0.00	1.28	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Bay of Plenty																		
Mean	5.18	5.18	4.93	4.60	3.76	4.71	3.12	3.13	2.98	3.03	2.71	3.29	2.95	2.91	3.21	2.50	2.22	2.54
Median	5.17	4.99	4.44	4.10	3.26	4.86	2.89	2.85	2.77	2.78	2.30	2.71	2.66	2.49	3.06	2.23	1.60	2.30
Spread	0.01	0.19	0.49	0.50	0.50	0.15	0.23	0.29	0.21	0.25	0.41	0.58	0.29	0.41	0.15	0.27	0.62	0.24
Std Er	11.51	11.51	11.22	9.63	8.91	11.51	5.59	5.66	6.71	5.39	4.62	6.55	7.42	7.47	6.83	5.95	6.25	6.95
Min.	0.02	0.20	0.18	0.17	0.10	0.01	0.18	0.09	0.03	0.06	0.08	0.25	0.12	0.09	0.01	0.03	0.06	0.02
Max.	16.49	16.37	18.30	14.28	12.58	15.07	11.74	11.82	11.54	10.63	9.51	10.73	9.55	9.89	14.06	10.67	10.62	10.53
TAE	5553	5563	5126	4833	4011	5107	3057	3088	2977	3083	2556	3203	3061	3021	3082	2379	2105	2541
% SAE >20%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tairawhiti																		
Mean	6.40	6.57	5.24	5.19	4.34	5.62	2.85	2.82	2.49	2.54	2.22	2.69	4.36	4.49	4.29	3.66	3.75	4.11
Median	6.05	6.11	3.99	4.73	3.69	5.16	2.28	2.27	1.51	1.88	1.62	2.28	4.22	4.19	3.57	3.24	3.25	3.87
Spread	0.35	0.46	1.25	0.46	0.65	0.46	0.57	0.55	0.97	0.65	0.61	0.41	0.14	0.30	0.72	0.42	0.50	0.24
Std Er	18.82	19.35	34.19	14.92	13.43	15.53	10.06	9.92	19.61	8.98	8.75	8.85	10.89	11.50	18.57	8.46	7.89	9.60
Min.	0.05	0.00	0.05	0.04	0.07	0.17	0.10	0.03	0.04	0.03	0.02	0.02	0.04	0.02	0.01	0.08	0.41	0.24
Max.	16.73	16.96	16.05	15.79	14.06	16.49	11.49	11.18	13.62	12.40	9.14	11.06	15.58	16.45	15.45	16.64	16.02	17.74

	Never smoked						Ex smoker						Regular smoker					
	STD (2y)	**FULL (3y)**	**DHB**	**CITY**	**DEP**	**RURAL**	**STD (2y)**	**FULL (3y)**	**DHB**	**CITY**	**DEP**	**RURAL**	**STD (2y)**	**FULL (3y)**	**DHB**	**CITY**	**DEP**	**RURAL**
TAE	4383	4483	3290	3312	2625	3750	1795	1776	1237	1552	1232	1710	2873	2981	2847	2195	2206	2550
% SAE >20%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hawke's Bay																		
Mean	6.16	6.15	4.70	4.81	4.65	6.11	3.81	3.76	2.65	3.47	3.07	3.87	3.33	3.35	3.36	2.72	2.76	3.21
Median	5.91	5.90	4.71	4.15	4.38	5.66	3.80	3.79	2.35	3.04	2.70	3.76	2.97	3.04	2.78	2.13	2.29	2.70
Spread	0.25	0.25	0.00	0.67	0.27	0.45	0.00	0.03	0.30	0.43	0.37	0.11	0.37	0.30	0.58	0.59	0.47	0.51
Std Er	8.61	8.72	14.11	7.35	6.47	8.20	4.46	4.56	7.86	4.82	3.56	4.67	5.54	5.71	7.75	4.16	4.54	5.22
Min.	0.04	0.23	0.08	0.18	0.39	0.21	0.16	0.13	0.03	0.43	0.20	0.20	0.12	0.00	0.24	0.00	0.06	0.00
Max.	16.98	15.14	11.26	13.64	13.16	16.34	8.00	7.99	9.69	8.64	7.36	7.56	14.00	13.20	8.78	11.74	10.75	15.16
TAE	9356	9387	7001	6851	6621	8846	4969	4918	3329	4275	3929	4967	4912	5011	4881	3580	3646	4539
% SAE >20%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mid Central																		
Mean	4.80	4.76	8.82	3.75	3.55	5.03	2.49	2.49	7.52	2.29	2.10	3.05	3.14	3.10	2.69	2.63	2.62	2.87
Median	4.98	4.97	8.62	3.61	3.29	5.16	2.14	2.13	7.47	1.61	1.62	2.48	2.77	2.61	2.28	2.46	2.18	2.60
Spread	0.18	0.21	0.20	0.14	0.26	0.14	0.34	0.36	0.04	0.68	0.48	0.57	0.37	0.50	0.41	0.17	0.44	0.27
Std Er	15.07	15.12	12.77	12.42	12.05	14.15	7.24	7.29	6.97	6.62	6.24	7.55	9.95	10.12	9.80	8.04	8.20	9.43
Min.	0.08	0.01	0.19	0.11	0.04	0.03	0.08	0.04	0.29	0.01	0.09	0.06	0.10	0.02	0.04	0.05	0.05	0.05
Max.	14.22	14.29	19.21	13.51	12.85	15.42	6.58	6.76	18.12	6.90	10.12	11.31	12.09	12.28	12.74	9.42	11.14	10.77
TAE	5435	5364	10084	3841	3612	5537	2761	2753	8378	2288	2009	3246	3198	3149	2402	2489	2574	2908
% SAE >20%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Taranaki																		
Mean	6.79	6.96	9.04	5.23	4.77	6.03	2.63	2.58	3.86	2.65	2.04	2.34	4.57	4.84	5.64	3.56	3.60	4.33
Median	6.54	6.62	8.85	4.85	4.18	5.56	2.19	2.16	3.27	2.13	1.55	1.91	4.49	4.65	5.70	3.50	3.33	3.87
Spread	0.25	0.34	0.19	0.38	0.59	0.47	0.44	0.41	0.59	0.52	0.48	0.44	0.09	0.18	0.05	0.06	0.27	0.46
Std Er	8.93	8.97	9.84	7.23	6.81	8.69	5.89	5.91	8.12	5.33	4.92	6.40	4.93	4.99	5.30	4.34	4.47	4.66
Min.	0.20	0.14	1.13	0.08	0.06	0.01	0.21	0.04	0.00	0.03	0.03	0.12	0.01	0.01	0.04	0.09	0.07	0.03
Max.	14.91	15.73	15.87	13.70	14.00	13.82	11.34	10.76	11.04	12.96	9.22	9.77	9.94	10.39	12.21	8.76	9.28	10.32

	Never smoked						Ex smoker						Regular smoker					
	STD (2y)	FULL (3y)	DHB	CITY	DEP	RURAL	STD (2y)	FULL (3y)	DHB	CITY	DEP	RURAL	STD (2y)	FULL (3y)	DHB	CITY	DEP	RURAL
TAE	8116	8295	10863	6063	5476	7216	2760	2708	4392	2526	1988	2500	5657	5924	6846	4354	4407	5304
% SAE >20%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Whanganui																		
Mean	4.29	4.25	7.05	3.83	3.50	4.58	3.95	3.97	5.02	3.59	3.32	4.39	3.00	2.93	3.73	3.20	3.23	3.05
Median	3.49	3.25	6.91	2.92	2.43	4.15	3.71	3.78	4.56	2.74	2.81	4.04	2.37	2.09	2.97	2.29	2.71	2.26
Spread	0.80	1.01	0.14	0.91	1.08	0.42	0.24	0.18	0.46	0.85	0.51	0.34	0.63	0.84	0.76	0.91	0.52	0.79
Std Er	7.88	7.88	10.15	6.63	6.23	7.87	5.08	5.07	8.10	4.95	4.17	5.61	5.09	5.33	6.31	4.52	4.53	4.98
Min.	0.12	0.14	0.06	0.04	0.14	0.21	0.18	0.11	0.39	0.12	0.03	0.18	0.04	0.06	0.14	0.06	0.15	0.01
Max.	11.56	12.74	15.73	14.43	11.48	12.61	14.79	14.40	12.13	17.48	16.08	16.63	14.15	13.45	10.08	18.20	16.35	15.55
TAE	1835	1810	3229	1453	1290	1933	1769	1763	2294	1311	1263	1973	835	813	1231	911	920	815
% SAE >20%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Capital and Coast																		
Mean	4.50	4.48	5.11	4.20	4.16	4.79	3.30	3.32	2.93	2.83	3.04	3.74	3.20	3.17	3.81	3.23	3.43	3.30
Median	3.24	3.35	4.26	3.07	3.14	3.49	2.97	3.13	2.64	2.26	2.55	3.41	2.51	2.31	2.74	2.66	2.52	2.53
Spread	1.25	1.13	0.85	1.13	1.02	1.30	0.33	0.19	0.29	0.58	0.49	0.34	0.68	0.86	1.07	0.56	0.90	0.77
Std Er	14.69	14.72	12.99	11.74	11.96	13.75	4.53	4.56	5.75	4.78	4.75	4.78	11.89	12.11	9.09	9.47	9.50	11.22
Min.	0.05	0.03	0.03	0.01	0.00	0.04	0.04	0.05	0.00	0.01	0.04	0.03	0.01	0.03	0.09	0.00	0.00	0.02
Max.	23.82	23.50	27.23	20.07	21.33	23.59	14.36	14.28	13.18	15.71	11.20	13.75	21.59	20.82	21.56	15.05	19.26	21.80
TAE	11550	11468	13453	9388	9973	12160	7113	7194	5680	5652	6238	8156	7899	7861	10086	7447	8132	8106
% SAE >20%	2.05	2.56	2.56	0.51	1.54	2.56	0.00	0.00	0.00	0.00	0.00	0.00	0.51	0.51	1.03	0.00	0.00	1.03
Hutt Valley																		
Mean	7.27	7.64	15.10	6.16	5.43	6.48	3.63	3.67	7.94	3.09	2.75	3.19	4.37	4.63	7.69	3.44	3.59	4.26
Median	7.80	8.52	12.80	6.02	5.21	6.65	3.66	3.77	6.97	2.55	2.50	3.10	4.30	4.66	6.44	3.20	2.73	3.88
Spread	0.53	0.88	2.30	0.15	0.22	0.18	0.03	0.10	0.97	0.54	0.26	0.09	0.07	0.03	1.26	0.23	0.86	0.38
Std Er	10.82	10.82	10.89	11.13	9.54	10.70	6.17	6.25	6.18	6.81	5.59	6.48	5.85	5.87	7.09	5.59	5.33	5.45
Min.	0.01	0.05	0.20	0.13	0.40	0.02	0.49	0.44	0.74	0.20	0.44	0.59	0.25	0.05	0.94	0.03	0.50	0.05
Max.	14.06	14.96	46.51	13.25	13.21	13.41	6.79	6.54	28.09	6.82	6.56	7.05	9.84	10.55	24.22	9.20	10.71	11.06

	Never smoked						Ex smoker						Regular smoker					
	STD (2y)	FULL (3y)	DHB	CITY	DEP	RURAL	STD (2y)	FULL (3y)	DHB	CITY	DEP	RURAL	STD (2y)	FULL (3y)	DHB	CITY	DEP	RURAL
TAE	2550	2651	4779	2030	1782	2215	1174	1177	2408	1020	861	1012	1425	1519	2400	1050	1007	1293
% SAE >20%	0.00	0.00	21.74	0.00	0.00	0.00	0.00	0.00	8.70	0.00	0.00	0.00	0.00	0.00	4.35	0.00	0.00	0.00
Wairarapa																		
Mean	5.08	5.05	5.09	3.35	3.24	4.95	4.06	3.99	4.45	3.22	3.08	4.31	2.44	2.40	2.60	2.22	2.20	2.25
Median	5.16	5.06	4.51	2.73	2.71	4.65	4.14	4.11	3.86	3.23	3.08	4.21	2.05	2.17	1.65	1.71	1.53	1.81
Spread	0.08	0.01	0.58	0.62	0.53	0.30	0.07	0.12	0.59	0.02	0.00	0.10	0.40	0.23	0.96	0.51	0.66	0.45
Std Er	11.28	11.36	28.93	8.43	8.49	9.45	8.02	7.74	16.60	5.91	5.54	6.76	6.42	6.63	14.83	6.96	6.92	6.35
Min.	0.05	0.19	0.00	0.23	0.01	0.34	0.10	0.05	0.07	0.06	0.02	0.13	0.08	0.11	0.08	0.06	0.01	0.13
Max.	10.26	10.01	14.82	11.84	11.84	10.94	11.34	11.35	13.52	9.15	12.16	11.23	8.28	7.42	12.72	8.06	11.83	10.12
TAE	4707	4696	4428	2910	2827	4451	3525	3483	3715	2677	2621	3700	1960	1986	1976	1613	1564	1753
% SAE >20%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Nelson Marlborough																		
Mean	6.97	7.00	5.33	5.19	4.87	6.48	4.00	3.94	3.88	3.50	3.15	3.98	3.61	3.66	3.02	2.93	2.83	3.31
Median	6.66	6.55	4.28	4.70	4.27	6.37	3.75	3.71	3.39	2.85	2.77	3.58	3.08	3.05	2.22	2.31	2.23	2.86
Spread	0.31	0.46	1.04	0.49	0.60	0.11	0.25	0.23	0.49	0.65	0.38	0.40	0.54	0.61	0.80	0.61	0.60	0.45
Std Er	9.78	9.65	14.68	8.39	7.79	10.38	5.63	5.70	11.60	5.38	4.52	6.77	5.84	5.75	4.74	4.93	5.37	5.69
Min.	0.18	0.01	0.05	0.06	0.04	0.10	0.04	0.02	0.01	0.12	0.06	0.05	0.11	0.00	0.00	0.00	0.01	0.07
Max.	39.62	40.68	38.61	39.05	36.14	38.35	17.01	17.24	14.72	16.52	14.18	15.90	22.22	23.05	23.50	22.13	21.57	22.06
TAE	21633	21734	16834	16060	15019	19876	10915	10786	10675	9406	8498	10700	11338	11570	8522	8348	7924	10122
% SAE >20%	0.61	0.61	0.61	0.61	0.61	0.61	0.00	0.00	0.00	0.00	0.00	0.00	0.61	0.61	0.61	0.61	0.61	0.61
Canterbury																		
Mean	2.50	2.56	11.72	1.98	2.02	2.29	1.92	1.83	6.19	1.31	1.33	1.90	1.67	1.72	5.73	1.42	1.77	1.67
Median	1.98	2.44	11.51	2.03	2.07	1.77	1.61	1.77	6.38	1.32	1.31	1.96	1.35	1.41	6.23	1.35	1.45	1.52
Spread	0.52	0.12	0.21	0.05	0.05	0.52	0.31	0.06	0.19	0.01	0.02	0.06	0.32	0.31	0.51	0.08	0.32	0.14
Std Er	7.98	7.95	7.70	7.76	7.32	8.20	4.37	4.41	3.94	4.44	4.12	4.80	4.57	4.51	4.71	4.46	4.55	4.54
Min.	0.03	0.03	4.73	0.08	0.04	0.29	0.29	0.19	0.09	0.19	0.03	0.20	0.23	0.01	0.43	0.10	0.35	0.21
Max.	6.35	5.89	18.54	6.00	6.09	5.63	4.28	4.26	10.17	3.14	3.44	3.91	4.93	5.80	9.35	3.92	4.44	5.09

	Never smoked						Ex smoker						Regular smoker					
	STD (2y)	**FULL (3y)**	**DHB**	**CITY**	**DEP**	**RURAL**	**STD (2y)**	**FULL (3y)**	**DHB**	**CITY**	**DEP**	**RURAL**	**STD (2y)**	**FULL (3y)**	**DHB**	**CITY**	**DEP**	**RURAL**
TAE	907	924	3989	585	594	776	649	622	2135	439	415	612	488	501	1914	442	502	467
% SAE >20%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
West Coast																		
Mean	6.30	6.16	6.94	5.15	4.17	5.97	3.03	3.03	3.32	2.71	2.11	3.06	3.63	3.47	3.86	2.82	2.67	3.22
Median	6.56	6.47	7.35	5.30	4.29	6.23	3.10	3.14	3.41	2.77	1.82	2.89	3.73	3.51	3.88	2.76	2.56	3.20
Spread	0.26	0.31	0.40	0.15	0.13	0.26	0.08	0.11	0.08	0.06	0.29	0.17	0.10	0.04	0.02	0.06	0.10	0.02
Std Er	4.87	4.78	9.38	4.99	4.49	5.03	3.74	3.73	6.44	2.90	3.08	3.82	3.66	3.51	5.29	4.16	4.37	3.74
Min.	0.32	0.09	0.17	0.02	0.04	0.02	0.02	0.00	0.04	0.02	0.01	0.02	0.14	0.19	0.15	0.15	0.00	0.32
Max.	14.09	13.75	16.46	13.39	12.33	14.07	9.88	9.83	11.44	8.95	8.43	10.31	7.51	7.61	9.78	7.22	6.74	7.43
TAE	27731	27131	30337	22593	17776	25920	12925	12973	14069	11343	8010	12626	15551	14829	16690	12028	11252	13815
% SAE >20%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
South Canterbury																		
Mean	4.60	4.57	8.68	5.42	4.81	4.55	4.69	4.61	7.02	4.10	4.24	4.83	4.95	4.88	6.44	5.76	5.35	4.88
Median	2.78	2.85	7.04	4.01	3.29	2.92	3.74	3.58	5.62	3.37	2.93	3.32	2.97	2.91	4.85	4.23	3.72	3.51
Spread	1.82	1.72	1.64	1.42	1.51	1.63	0.96	1.04	1.41	0.73	1.31	1.51	1.98	1.97	1.59	1.53	1.62	1.38
Std Er	12.19	12.06	19.80	11.62	10.39	13.42	9.60	9.62	16.89	8.82	7.60	11.42	6.20	6.17	8.06	6.81	6.95	6.42
Min.	0.03	0.09	1.07	0.06	0.18	0.02	0.11	0.16	0.13	0.07	0.41	0.22	0.15	0.04	0.08	0.00	0.23	0.19
Max.	39.39	39.22	45.31	35.59	31.79	31.89	21.94	21.59	32.63	18.28	21.29	19.35	18.72	18.89	24.25	18.58	18.96	17.39
TAE	969	949	2220	1152	1002	988	976	962	1593	763	797	1017	884	850	1249	1084	1062	904
% SAE >20%	1.89	1.89	3.77	1.89	1.89	1.89	1.89	1.89	5.66	0.00	1.89	0.00	0.00	0.00	1.89	0.00	0.00	0.00
Southern																		
Mean	6.30	6.44	7.60	5.00	4.80	5.86	3.49	3.44	5.55	3.32	3.02	3.38	3.48	3.67	4.18	2.80	2.79	3.29
Median	6.22	6.32	6.94	4.71	4.73	5.81	3.60	3.54	5.55	2.95	2.60	2.98	3.31	3.60	3.22	1.97	2.39	2.75
Spread	0.07	0.12	0.66	0.29	0.07	0.04	0.10	0.10	0.00	0.38	0.42	0.40	0.17	0.06	0.95	0.83	0.40	0.54
Std Er	8.72	8.71	8.78	7.11	8.31	9.04	2.76	2.81	2.52	2.55	2.86	3.15	7.65	7.52	8.24	6.00	7.05	7.94
Min.	1.39	1.51	0.59	0.28	0.01	0.08	0.23	0.09	1.21	0.24	0.18	0.04	0.10	0.06	0.52	0.19	0.04	0.13
Max.	15.61	16.01	19.53	12.92	12.77	14.05	11.85	11.59	21.71	10.70	16.14	12.46	12.63	12.84	11.86	11.09	11.74	12.55

	Never smoked						**Ex smoker**						**Regular smoker**					
	STD (2y)	**FULL (3y)**	**DHB**	**CITY**	**DEP**	**RURAL**	**STD (2y)**	**FULL (3y)**	**DHB**	**CITY**	**DEP**	**RURAL**	**STD (2y)**	**FULL (3y)**	**DHB**	**CITY**	**DEP**	**RURAL**
TAE	2883	2951	3573	2007	1915	2624	1458	1420	2524	1367	1113	1394	1523	1615	1685	1107	1116	1418
% SAE >20%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

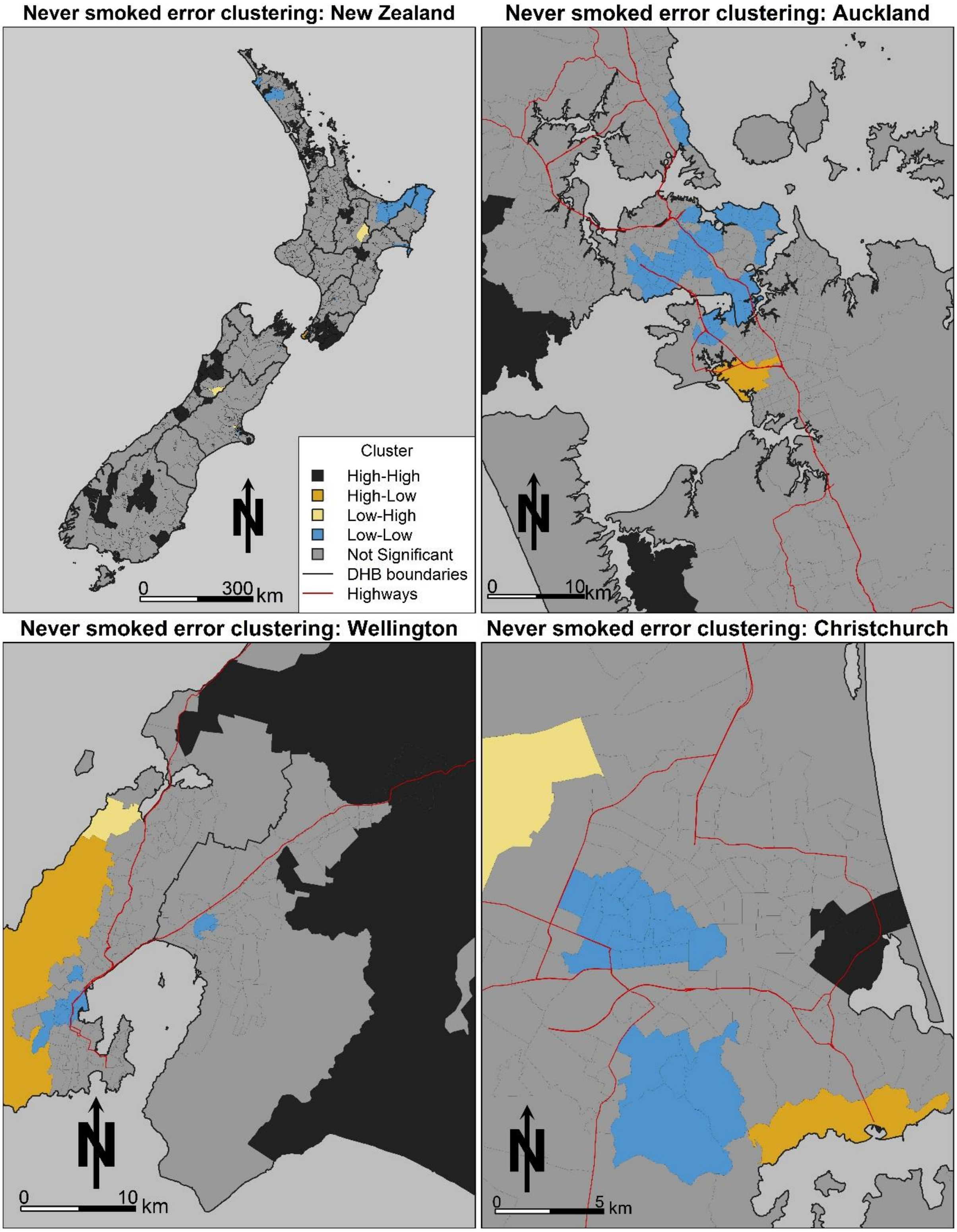

Figure C.2: Clustering within the errors for those who have never smoked using Moran's I.

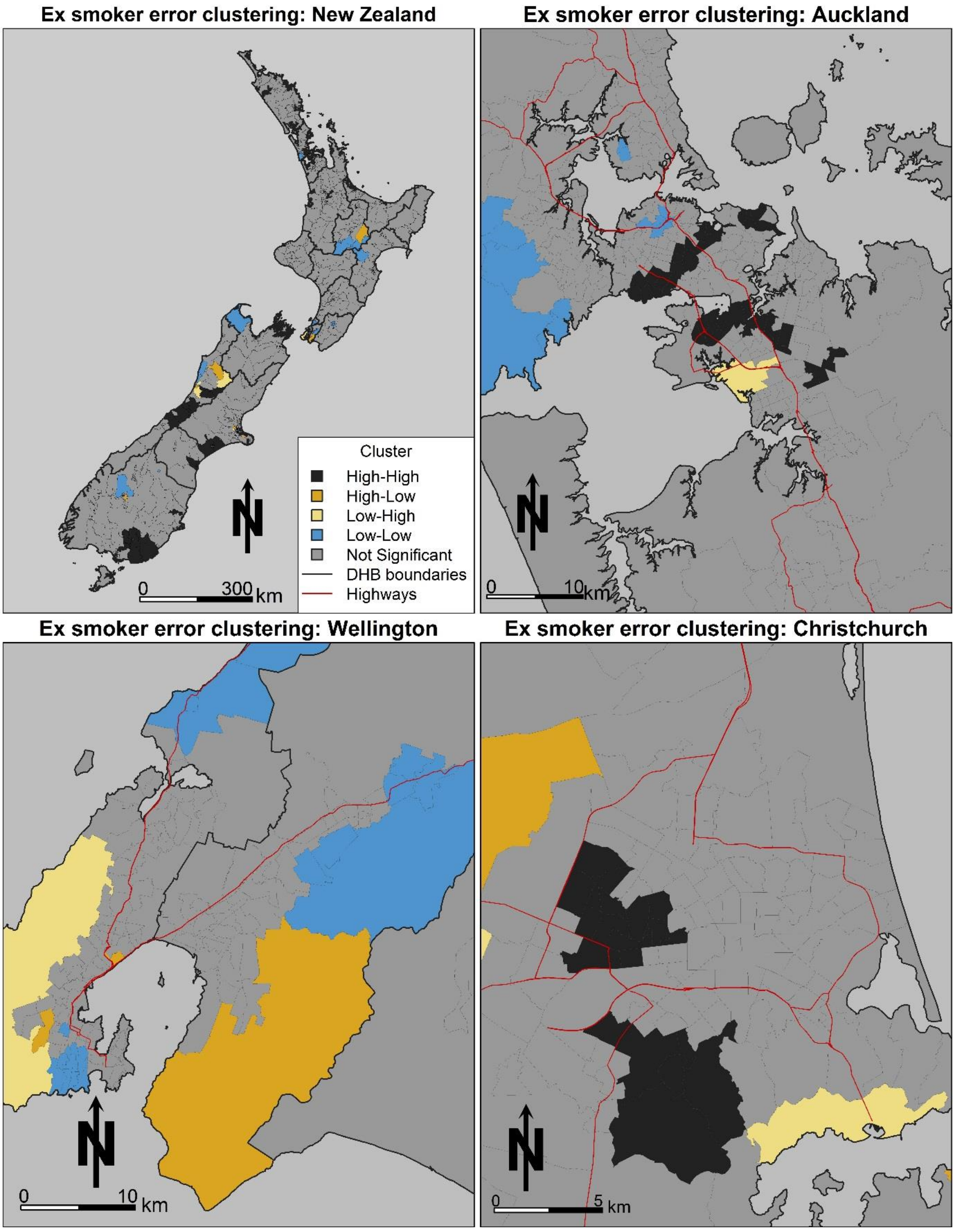

Figure C.3: Clustering within the errors for ex smokers using Moran's I.

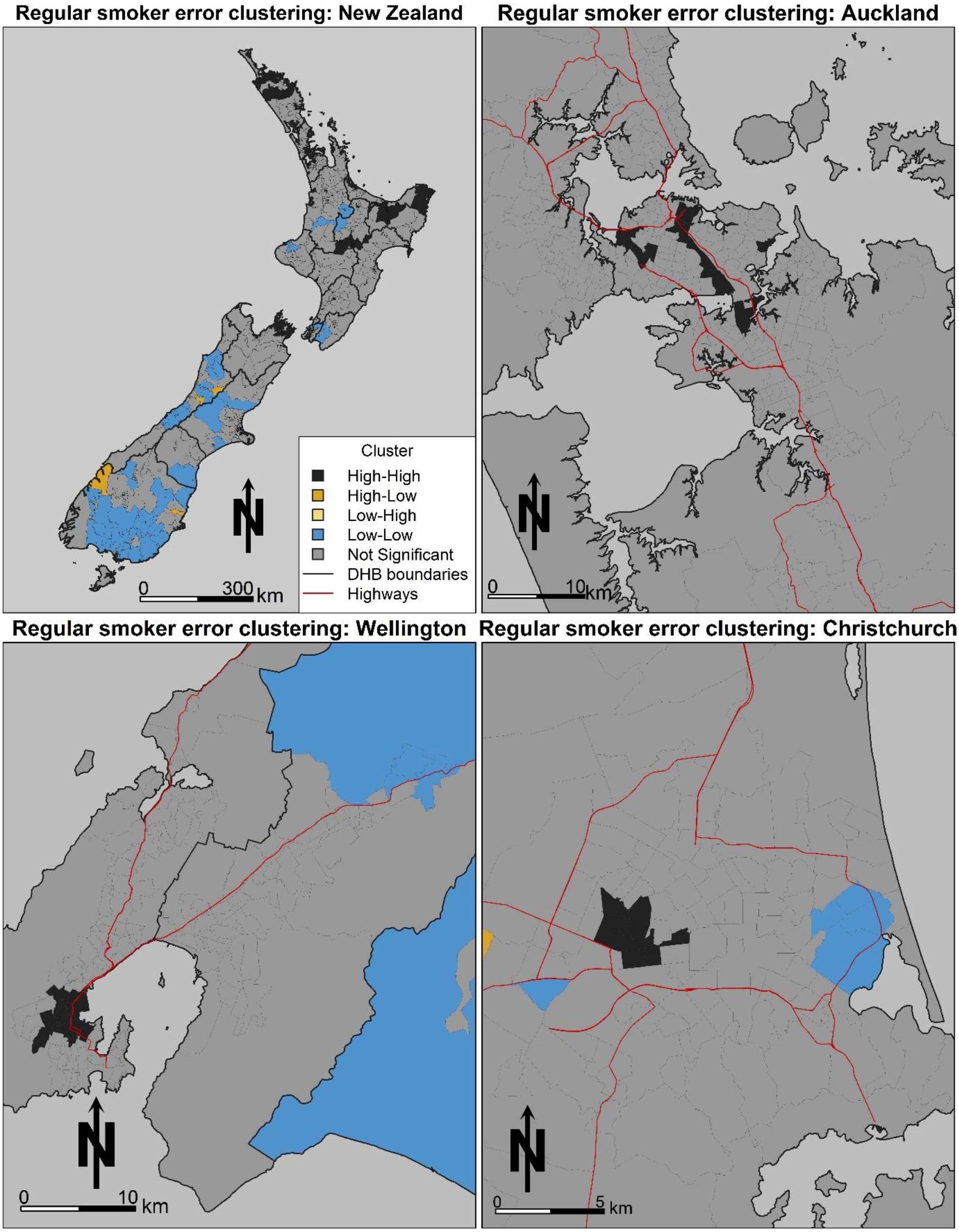

Figure C.4: Clustering within the errors for regular smokers using Moran's I.

Appendix D Additional SMSM results

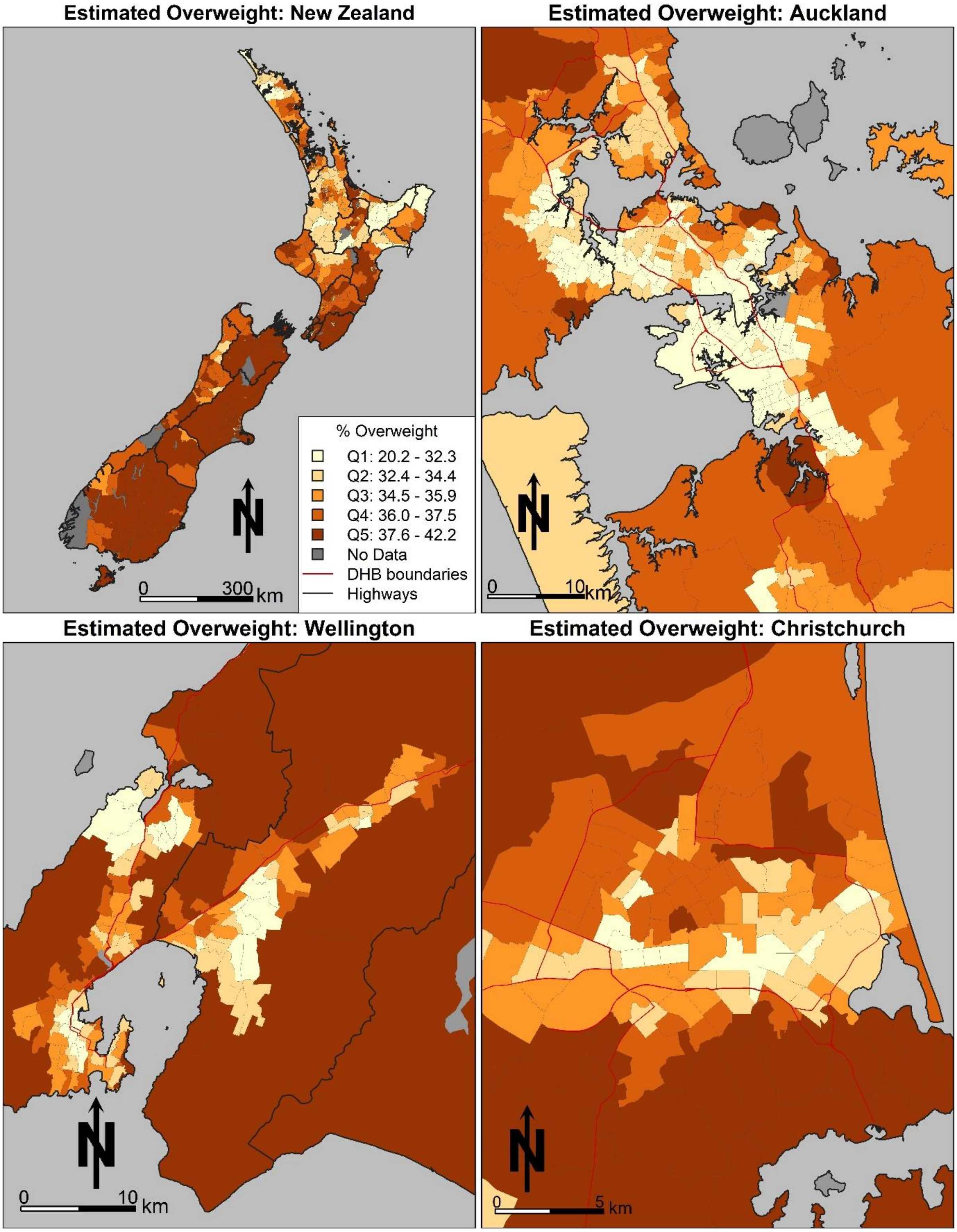

Figure D.1: Estimated overweight from SimAotearoa.

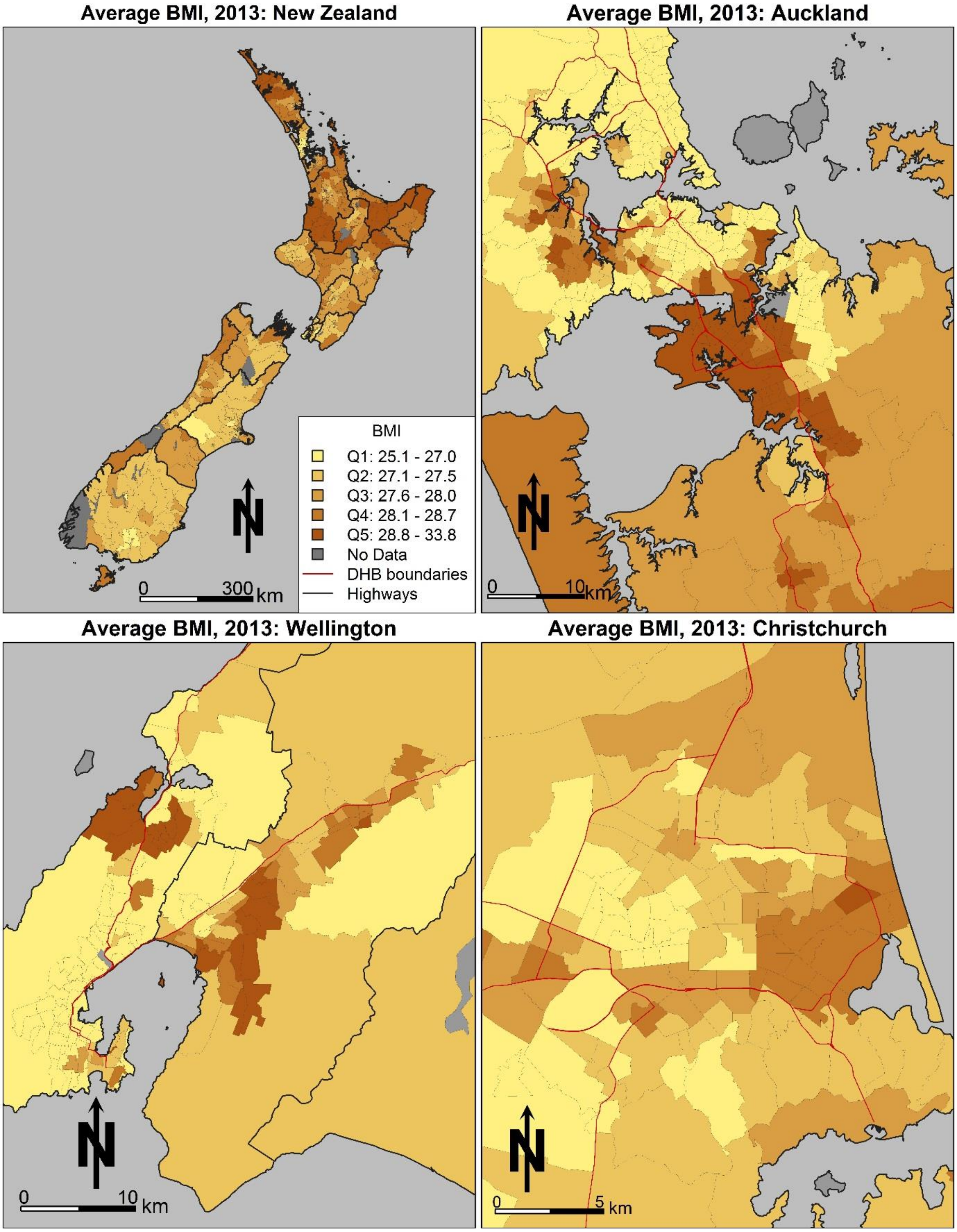

Figure D.2: Estimated average BMI from SimAotearoa.

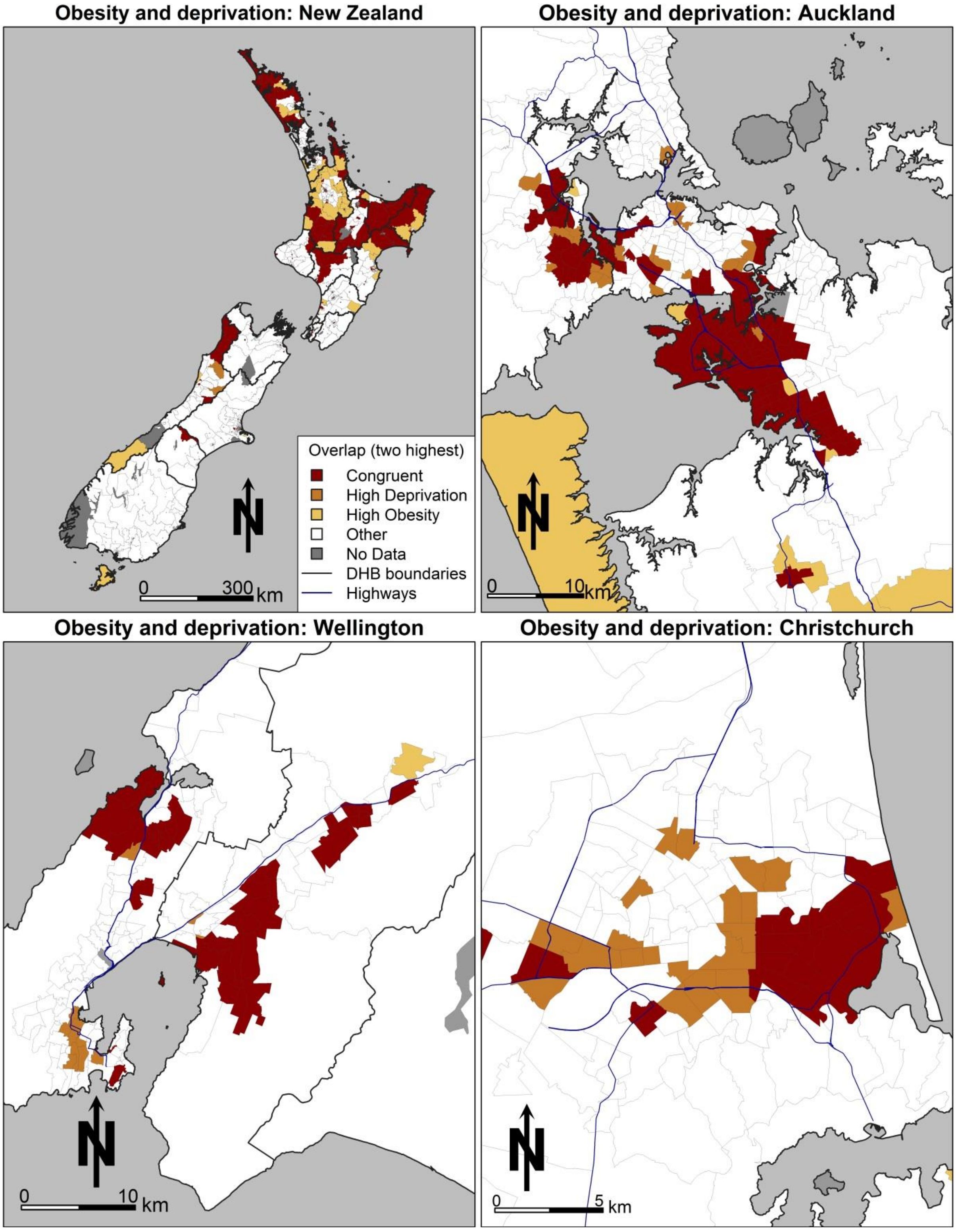

Figure D.3: Overlay of deprivation and estimated obesity, two highest quintile categories.

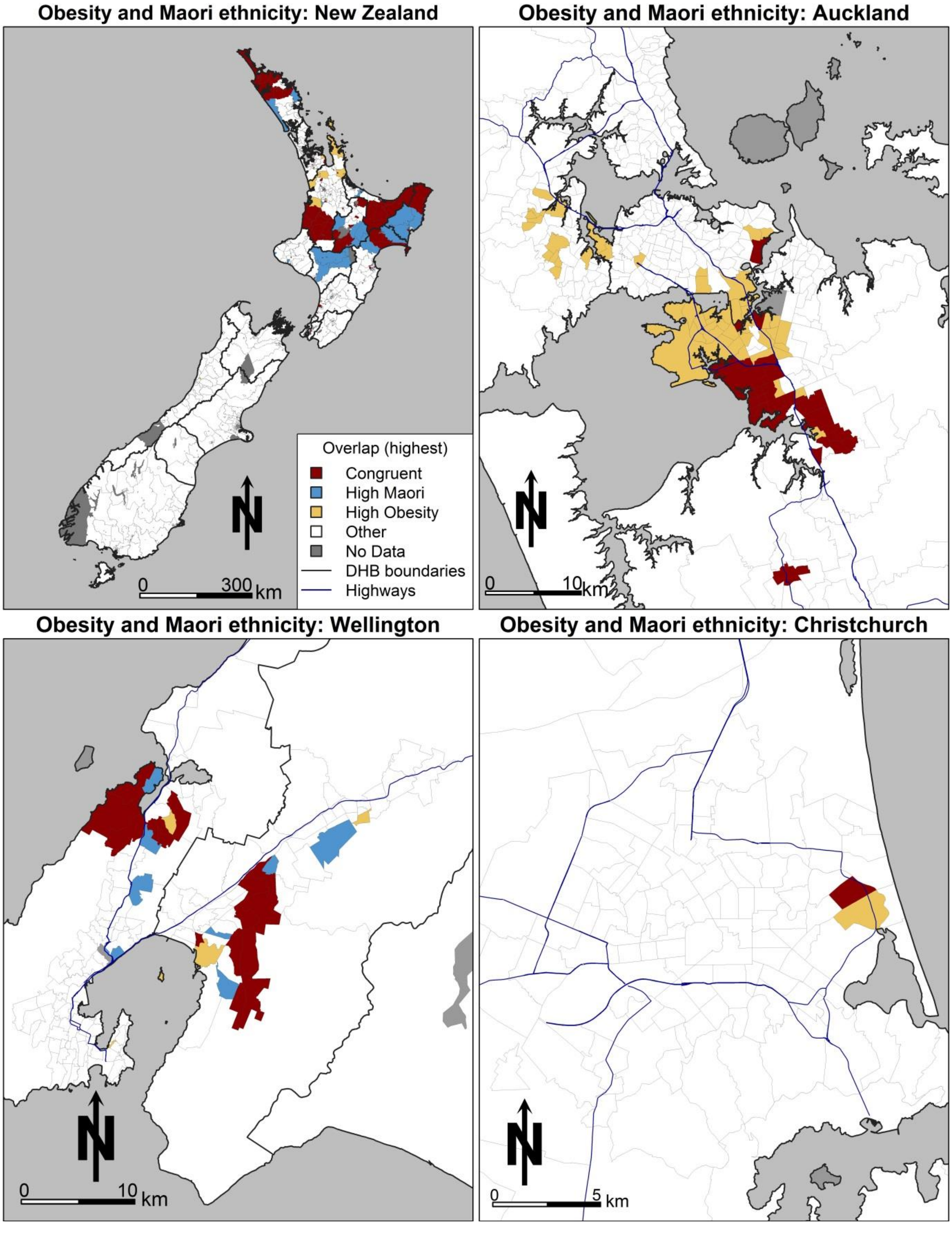

Figure D.4: Overlay of Māori ethnicity and estimated obesity, for the highest quintile categories.

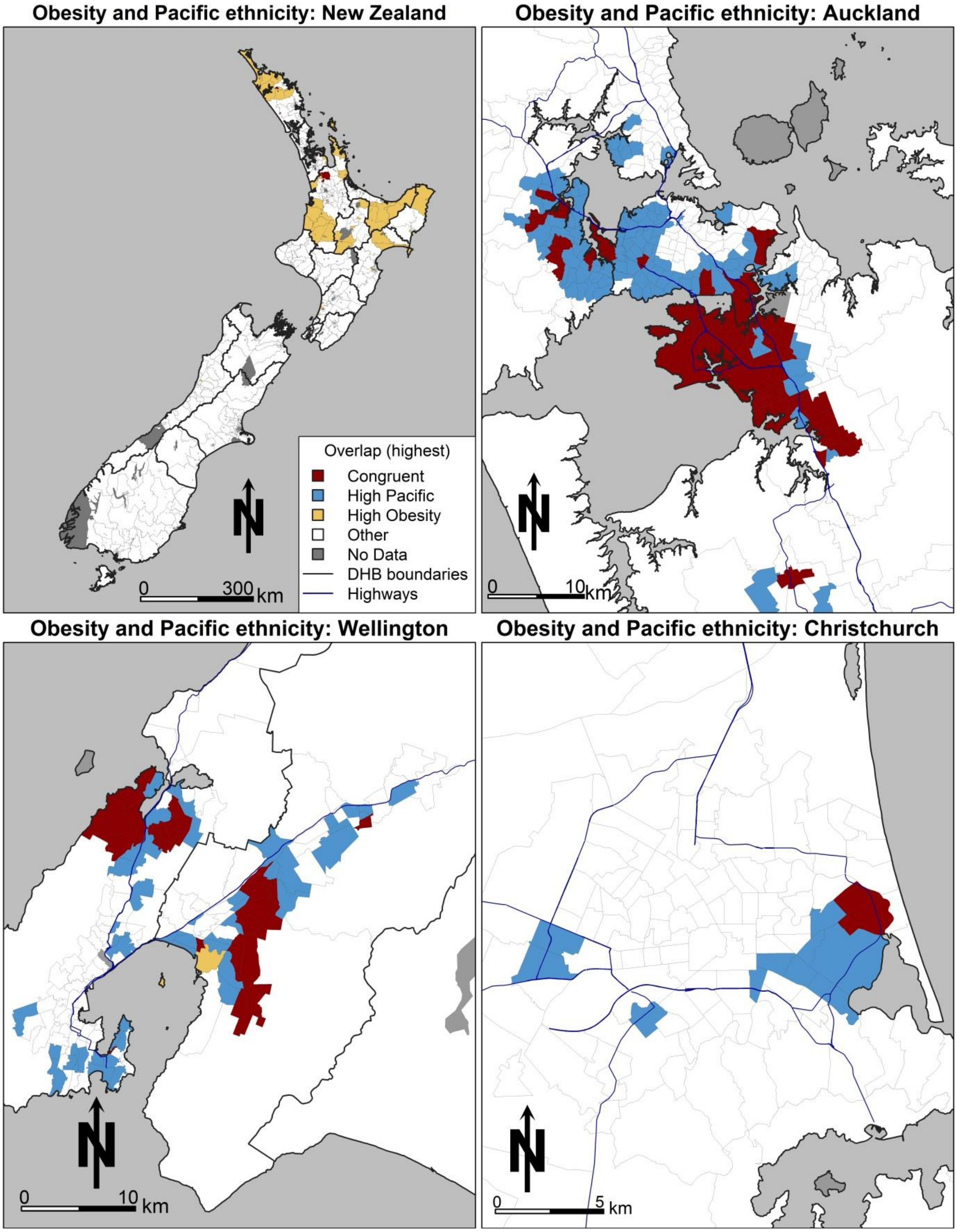

Figure D.5: Overlay of Pacific ethnicity and estimated obesity, for the highest quintile categories.

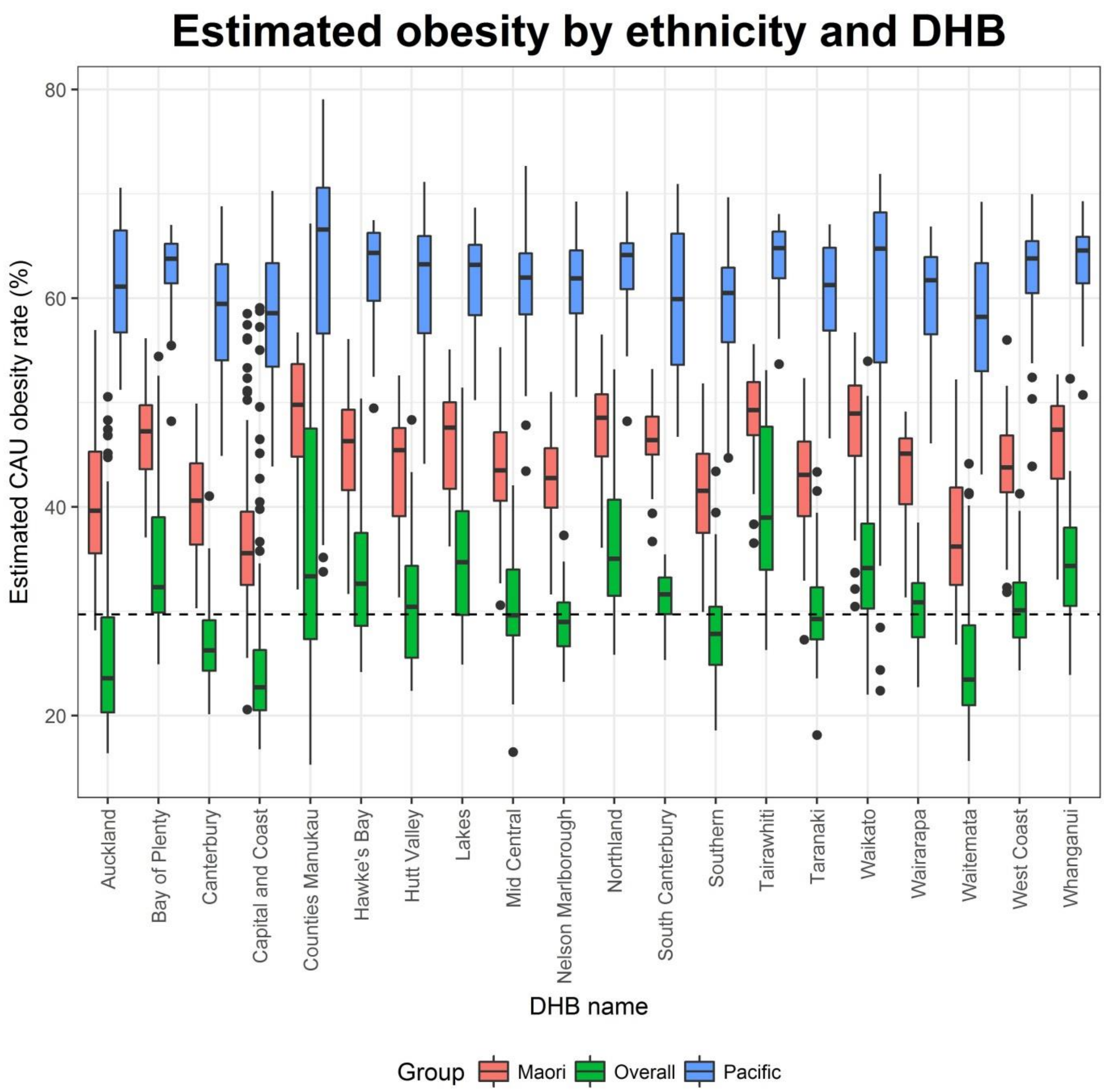

Figure D.6: Spread of estimated obesity rates by ethnicity and DHB.

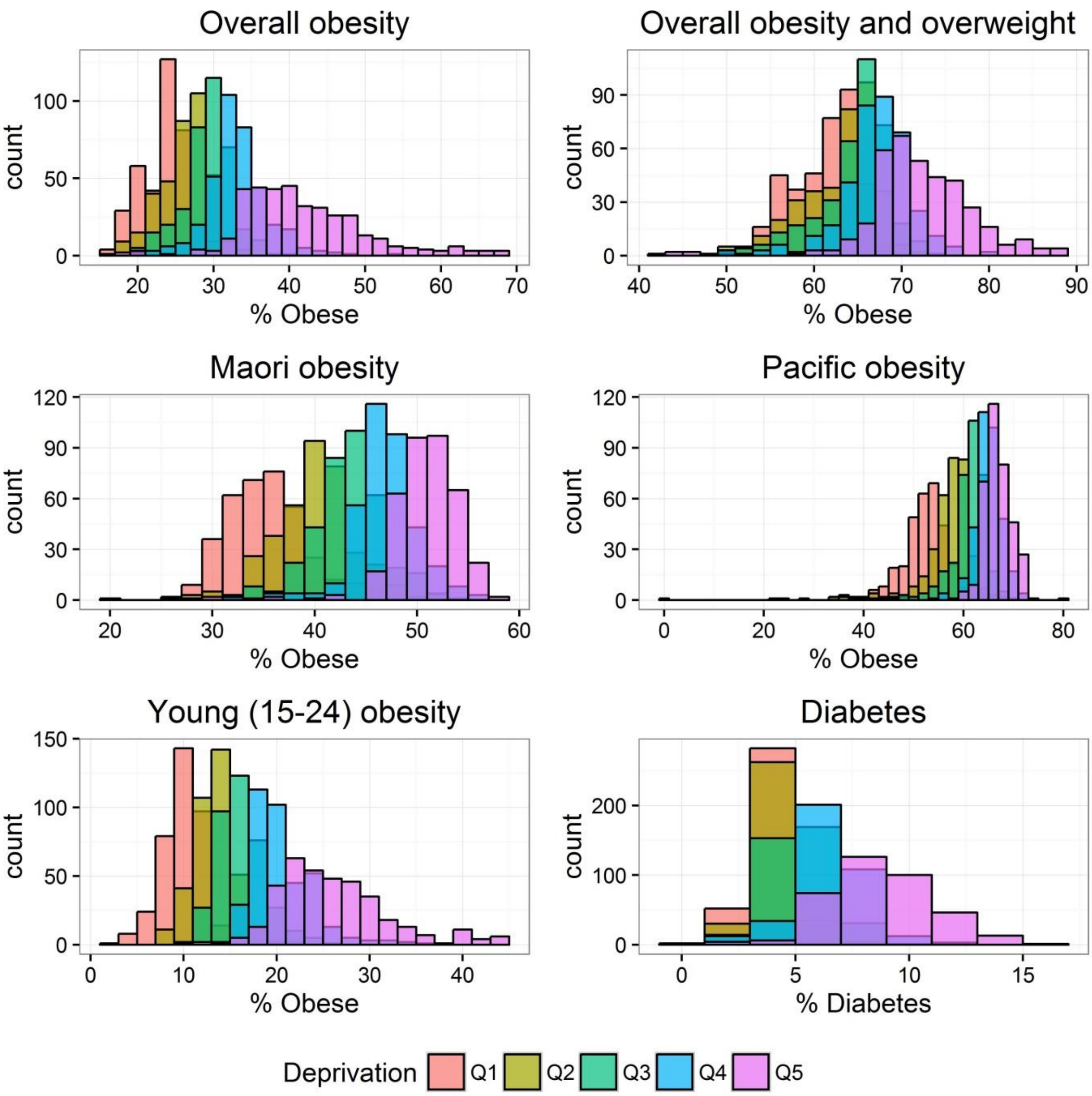

Figure D.7: Comparison of obesity and diabetes rates by CAU at different levels of deprivation.

Appendix E Additional projection results

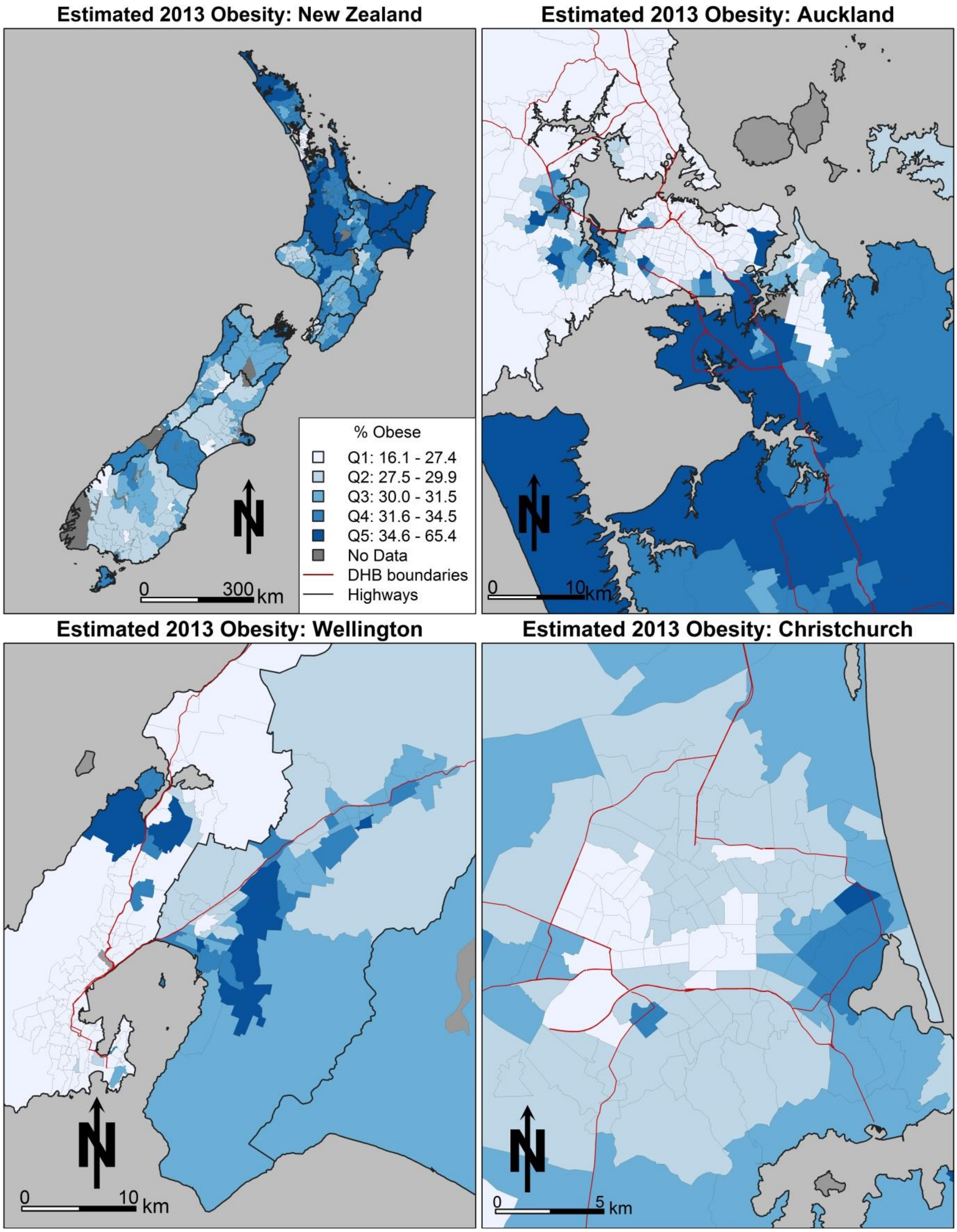

Figure E.1: Estimated obesity in 2013.

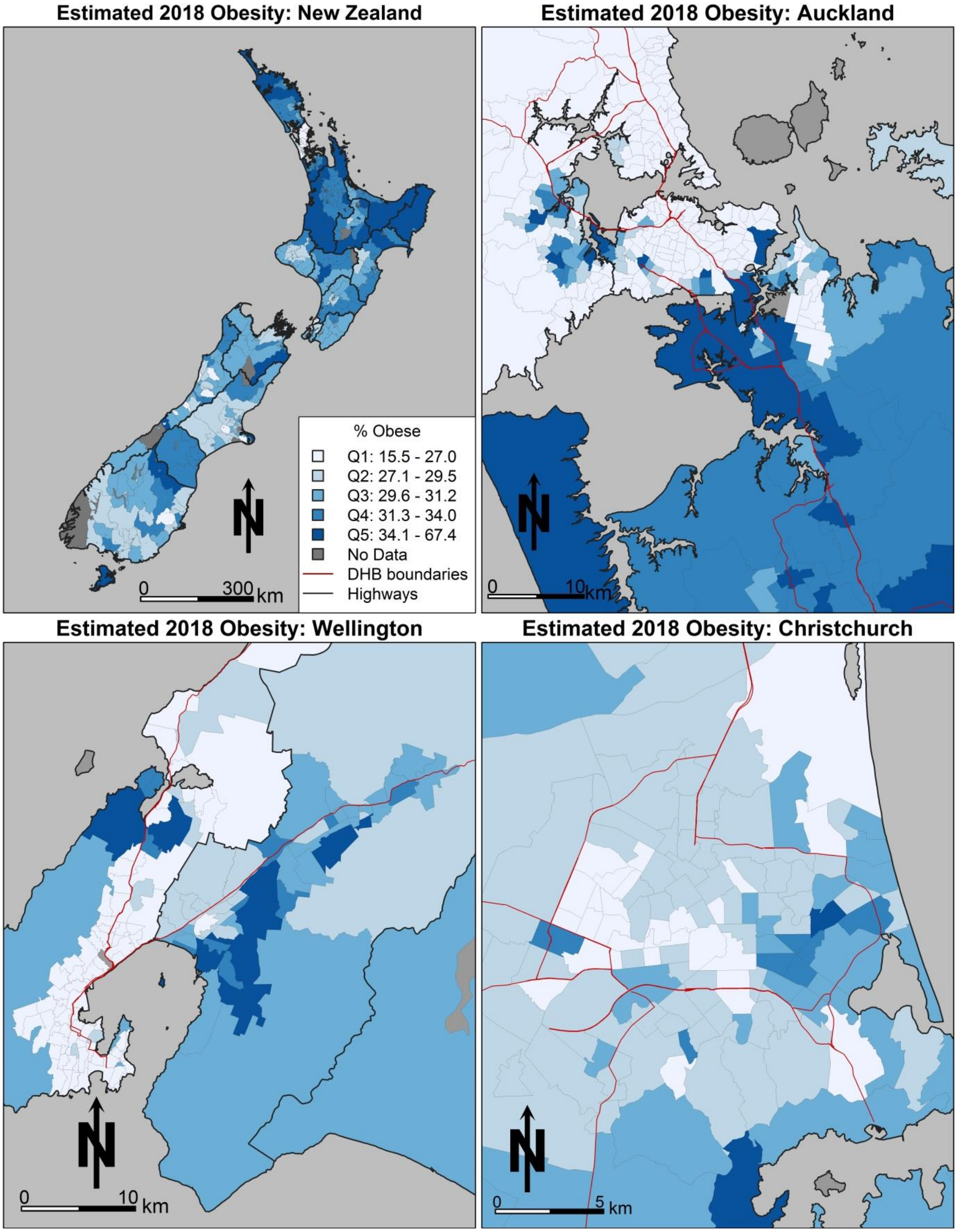

Figure E.2: Estimated obesity in 2018.

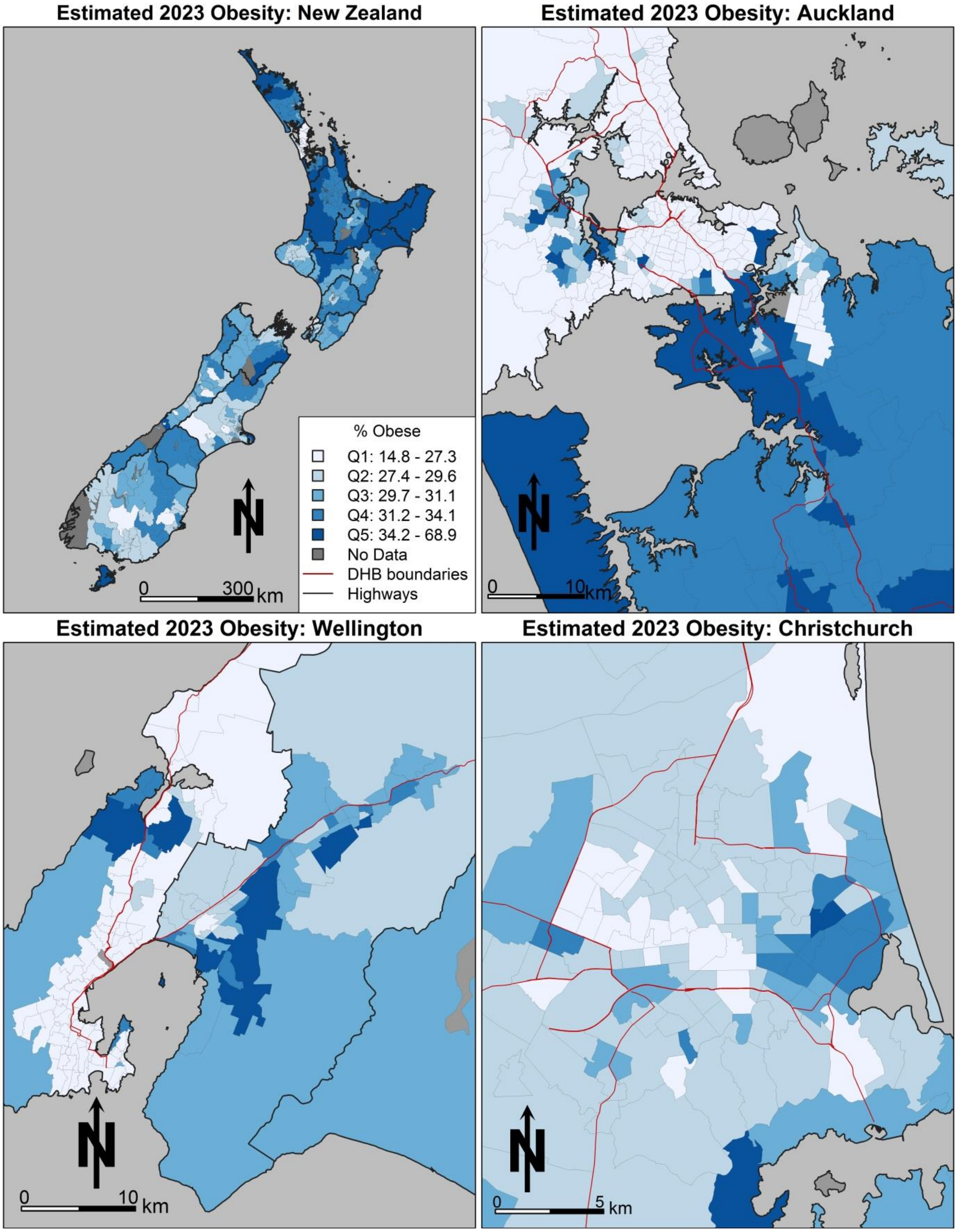

Figure E.3: Estimated obesity in 2023.